410-57, Assignment #1 Anamitra Bhattacharyya

INTRODUCTION

This is assignment is part of an overall project to build statistical regression models related to modeling sales prices of dwellings in Ames, Iowa. This assignment specifically deals with performing an exploratory data analysis (EDA) of an observational data set from the Ames Assessor's Office used in obtaining values for individual residential properties sold in Ames, Iowa between 2006 and 2010. As described in the data dictionary, the Ames data set comprises 2930 observations (properties sold) with 82 variables, comprising: 23 nominal, 23 ordinal, 14 discrete, and 20 continuous variables (with 2 additional observational identifiers). The goal of this EDA assignment is to evaluate and identify potential variables that are predictors of sales prices in the Ames housing market. The overall steps in the assignment comprise:

- a) Data Survey
- b) Data Quality Check
- c) Initial Exploratory Data Analysis

RESULTS

1. Examining Variables in Ames Housing dataset

For the purposes of this assignment, a selection of 20 variables were chosen as potential predictors, from prior knowledge and experience

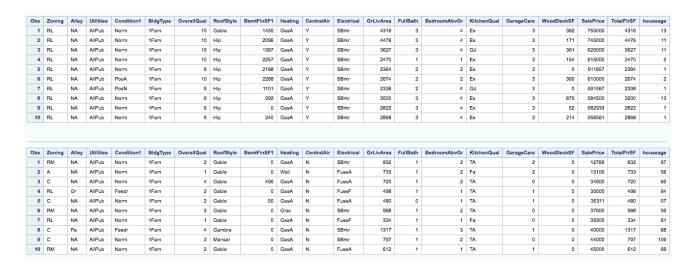
- 1. Continuous and discrete variables:
 - (a) 5 continuous variables chosen: TotalFlrSF, GrLivArea, BsmtFinSF1, WoodDeckSF, SalePrice.
 - (b) 4 Discrete variables chosen: houseage, FullBath, BedroomAbvGr, GarageCars.
- 2. Categorical variables, 11 were chosen: Zoning KitchenQual OverallQual CentralAir Alley Condition1 BldgType Heating Electrical Utilities RoofMatl.

Included derived variables TotalFIrSF (sum of FirstFIrSF and SecondFIrSF) and houseage (YrSold - YearBuilt).

2. Using PROC SORT procedure

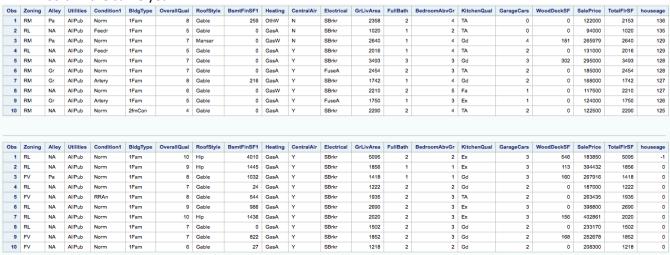
- a) PROC SORT by saleprice
- 2 observations above \$700,000 (outliers, see upper table below)
- 2 observations below \$20,000 (outliers, see lower table below)

Looking at all 2930 SalePrice observations indicates they all have a sale price associated with them.



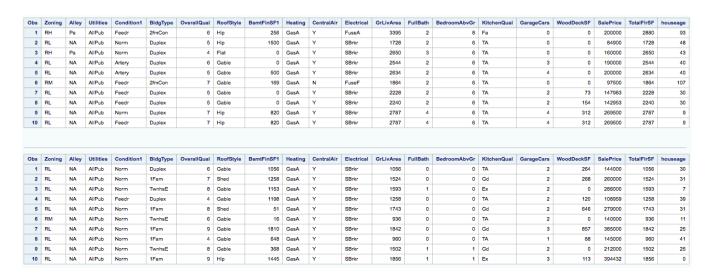
b) PROC SORT by houseage

Ascending sort reveals a house with a -1 year's age (which is an erroneous value). While there are numerous houses of zero age, these are likely new construction that were likely built and sold in the same year.



c) PROC SORT by BedroomAbvGr

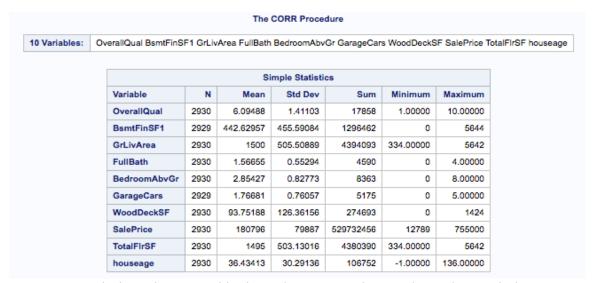
Ascending reveals some houses with zero bedrooms above ground (see lower output table below), these are either spurious and are errors, or alternatively have the bedrooms in the basement (possibly a ranch style). Using descending sort there is also one house with 8 bedrooms from a two-family conversion (see lower output table), but this is an outlier.



Conclusion: We have a reasonable set of variables with which to predict the sales prices including certain variables that were created such at TotalFISF and houseage. These additional variables were created to provide a better idea of overall square footage of homes and ages of homes. The sales prices in the entire dataset were reviewed and there were none that were zero or negative prices. However, there are outliers in the sales prices of residences in the upper and lower sales range. The houseage data was reviewed and revealed an error (e.g. a value of -1 from one residence), while others had a zero age, mostly likely brand new homes. The BedroomAbvGr (number of bedrooms above ground) revealed a house with 8 bedrooms, which is an outlier, arising from a 2-family duplex conversion.

3. Correlation

Numeric variables (10): OverallQual, BsmtFinSF1, GrLivArea, FullBath, BedroomAbvGr, GarageCars, WoodDeckSF, SalePrice, TotalFlrSF, houseage. See output table below.



Comment on which predictor variables have the strongest linear relationships with the response variable, Y?

The predictor variables with the best R^2 coefficient are OverallQual (0.79926), TotalFlrSF (0.71359) and GrLivArea (0.70678); this is followed by GarageCars (0.64788) and FullBath

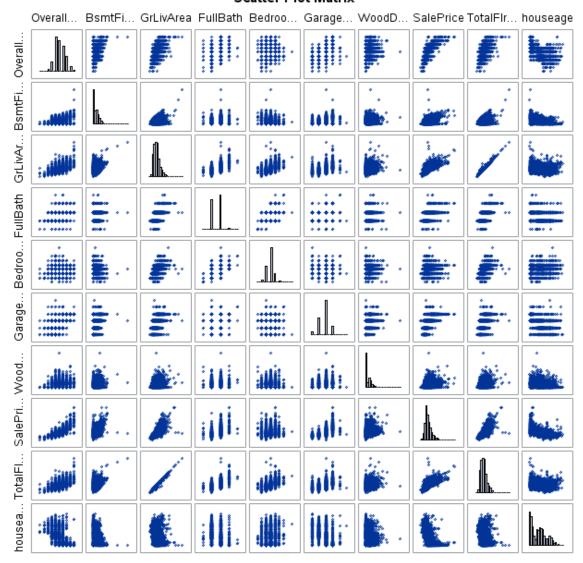
(0.54560), BsmtFinSF1 (0.43291) and WoodDeckSF (0.32714). The relationship between saleprice and BedroomAbvGr (0.14391), seems to have the most surprisingly low correlation. There is also a reasonable negative correlation between saleprice and houseage (-0.55891), indicating newer houses have a higher sale price *versus* older ones. See Pearson correlation coefficients table below.

Pearson Correlation Coefficients Prob > r under H0: Rho=0 Number of Observations										
	OverallQual	BsmtFinSF1	GrLivArea	FullBath	BedroomAbvGr	GarageCars	WoodDeckSF	SalePrice	TotalFirSF	houseage
OverallQual	1.00000 2930	0.28412 <.0001 2929	0.57056 <.0001 2930	0.52226 <.0001 2930	0.06329 0.0006 2930	0.59954 <.0001 2929	0.25566 <.0001 2930	0.79926 <.0001 2930	0.57773 <.0001 2930	-0.59702 <.0001 2930
BsmtFinSF1	0.28412 <.0001 2929	1.00000	0.20963 <.0001 2929	0.07777 <.0001 2929	-0.11896 <.0001 2929	0.25548 <.0001 2928	0.22401 <.0001 2929	0.43291 <.0001 2929	0.21672 <.0001 2929	-0.27847 <.0001 2929
GrLivArea	0.57056 <.0001 2930	0.20963 <.0001 2929	1.00000 2930	0.63032 <.0001 2930	0.51681 <.0001 2930	0.48883 <.0001 2929	0.25015 <.0001 2930	0.70678 <.0001 2930	0.99579 <.0001 2930	-0.24251 <.0001 2930
FullBath	0.52226 <.0001 2930	0.07777 <.0001 2929	0.63032 <.0001 2930	1.00000 2930	0.35949 <.0001 2930	0.47818 <.0001 2929	0.17957 <.0001 2930	0.54560 <.0001 2930	0.63354 <.0001 2930	-0.46890 <.0001 2930
BedroomAbvGr	0.06329 0.0006 2930	-0.11896 <.0001 2929	0.51681 <.0001 2930	0.35949 <.0001 2930	1.00000 2930	0.09136 <.0001 2929	0.02971 0.1079 2930	0.14391 <.0001 2930	0.51276 <.0001 2930	0.05423 0.0033 2930
GarageCars	0.59954 <.0001 2929	0.25548 <.0001 2928	0.48883 <.0001 2929	0.47818 <.0001 2929	0.09136 <.0001 2929	1.00000	0.24123 <.0001 2929	0.64788 <.0001 2929	0.49734 <.0001 2929	-0.53760 <.0001 2929
WoodDeckSF	0.25566 <.0001 2930	0.22401 <.0001 2929	0.25015 <.0001 2930	0.17957 <.0001 2930	0.02971 0.1079 2930	0.24123 <.0001 2929	1.00000 2930	0.32714 <.0001 2930	0.25278 <.0001 2930	-0.22858 <.0001 2930
SalePrice	0.79926 <.0001 2930	0.43291 <.0001 2929	0.70678 <.0001 2930	0.54560 <.0001 2930	0.14391 <.0001 2930	0.64788 <.0001 2929	0.32714 <.0001 2930	1.00000	0.71359 <.0001 2930	-0.55891 <.0001 2930
TotalFirSF	0.57773 <.0001 2930	0.21672 <.0001 2929	0.99579 <.0001 2930	0.63354 <.0001 2930	0.51276 <.0001 2930	0.49734 <.0001 2929	0.25278 <.0001 2930	0.71359 <.0001 2930	1.00000 2930	-0.25691 <.0001 2930
houseage	-0.59702 <.0001 2930	-0.27847 <.0001 2929	-0.24251 <.0001 2930	-0.46890 <.0001 2930	0.05423 0.0033 2930	-0.53760 <.0001 2929	-0.22858 <.0001 2930	-0.55891 <.0001 2930	-0.25691 <.0001 2930	1.00000

What do you notice about the relationship between the numeric correlation measure and the graphical relationship in the scatterplot?

While the tabular view of the correlation produces a discrete value for the R² coefficient, in contrast the scatterplot gives a better idea of the distribution, range and scatter of data points. See scatter plot matrix below:

Scatter Plot Matrix



Which predictor variable do you think will be the best single predictor variable. Why? Which will be the worst and why? Are there high correlations within the set of potential predictor variables? This is a primary way to see/identify multicollinearity.

OverallQual (0.79926) is the best single predictor based solely on its highest correlation coefficient, and conversely, the worst is BedroomAbvGr (0.14391). There are other variables displaying high correlations with saleprice in this sample and they include: TotalFlrSF (0.71359) and GrLivArea (0.70678), GarageCars (0.64788) and FullBath (0.54560), in that order. These latter variables are candidates for multilinearity. See the Pearson Correlation Coefficient table shown earlier, and note the row or column for saleprice.

Is the correlation coefficient sufficient information to make a decision regarding a predictor variable and it's usefulness in developing a predictive model? Why?

The correlation coefficient alone is not always a good measure of usefulness for a predictor variable. One needs to take into account the distribution and variability within that dataset. For example, in the case of OverallQual and saleprice, there is a lot of variability in

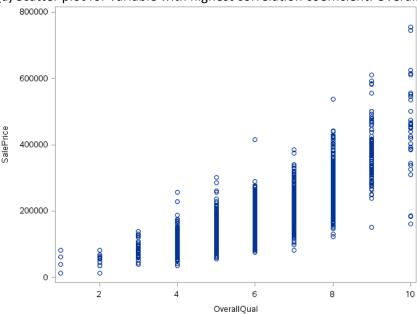
saleprice for homes scoring as being excellent quality. This can be seen from the scatterplot but is difficult to observe merely from looking at the correlation coefficient alone. In addition for a variable such as OverallQual, the conferring of a particular score is not immediately transparent; that is, it may be somewhat subjective - what differentiates a score of '10' from one of '8'?

Conclusion: There are candidate variables that from the correlation coefficient matrix indicate may be predictors for sales price of homes, though there is some variability suggested from the scatter plots.

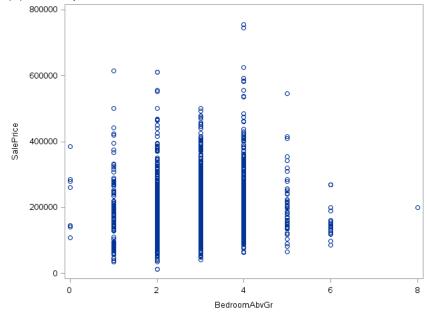
4. Scatter Plots

To investigate the scatter variability further, individual scatter for certain variables was studied.

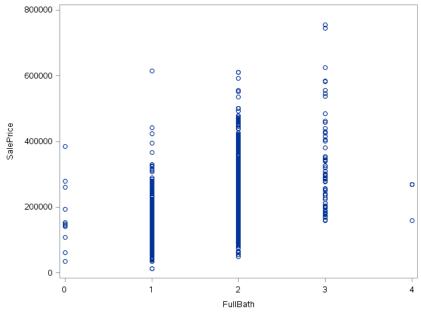
(a) Scatter plot for variable with highest correlation coefficient: OverallQual (0.79926)



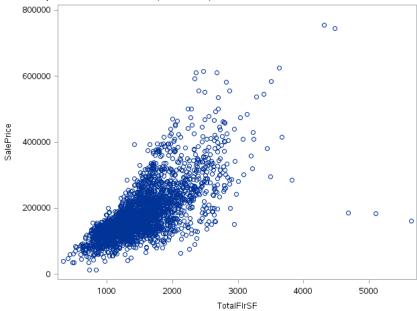
(b) Scatter plot for variable with lowest correlation coefficient: BedroomAbvGr (0.14391)



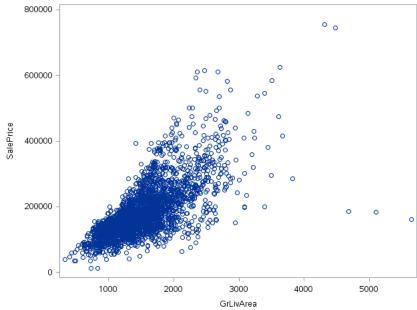
(c) Scatter plot for variable with correlation closet to 0.5: FullBath (0.54560)



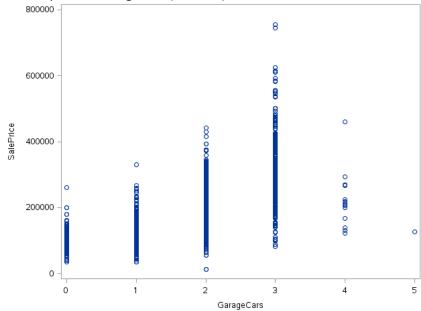
Scatter plot for TotalFlrSF (0.71359)



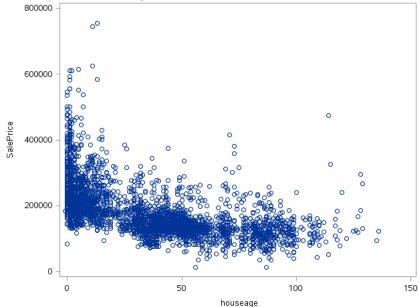
Scatter plot for GrLivArea (0.70678)



Scatter plot for GarageCars (0.64788)



Scatter plot for houseage (-0.55891)



Conclusion: Irrespective of the value of the correlation coefficients the individual scatter plots highlight that although there is a correlation evident, one needs to be wary since there is quite a lot of variation present. This variation is manifest in the form of extensive scatter (e.g. fan-tailing in TotalFlrSF, GrLivArea).

5. LOESS Plots

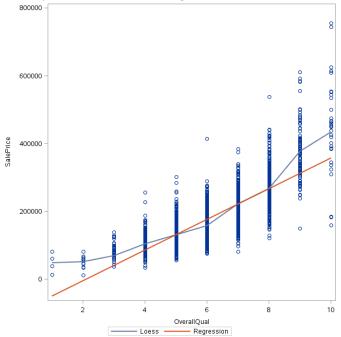
Comment on why we are interested in the LOESS scatterplots and what they are showing us?

LOESS (locally weighted scatterplot smoothing) augments linear regression models, when data sometimes display nonlinear patterns. LOESS sometimes provides a better curve-fit to nonlinear patterns. It does this by fitting simple models to localized subsets of the data to build up a function, whereas a linear regression model will specify a global function to the entire dataset.

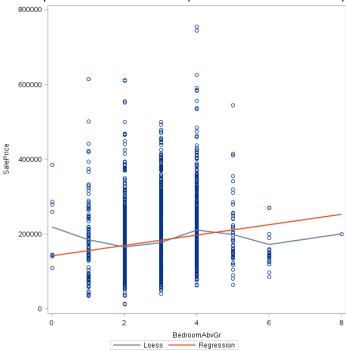
Below are the LOESS plots for:

- a) OverallQual (highest correlation earlier)
- b) BedroomAbvGr (lowest correlation earlier)
- c) FullBath (correlation closest to 0.5 from earlier)

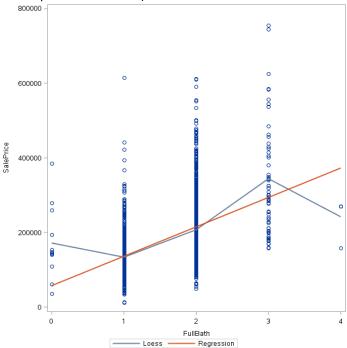
LOESS plot for OverallQual (highest correlation earlier)



LOESS plot for BedroomAbvGr (lowest correlation earlier)



LOESS plot for FullBath (correlation closest to 0.5 from earlier)



Conclusion: Since some of our variables display wide variability, while the linear model tries to fit the entire data for a variable a produces poor fit to the data, as is, the LOESS model due to it localized approach (point-by-point or category-by-category) fits some of the distributions better. Over parts of the datasets shown above, the LOESS and linear regression lines coincide, while at other times the lines diverge.

6. Analysis of categorical variables

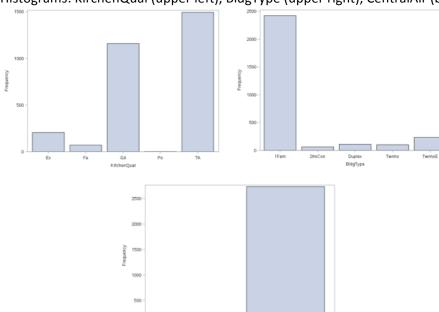
Using PROC REQ and histograms to display three specific categorical variables: KitchenQual, BldgType and CentralAir. The frequency distribution tables for these variables are shown below, followed by their respective histograms.

The FREQ Procedure							
KitchenQual	Frequency	Percent	Cumulative Frequency	Cumulative Percent			
Ex	205	7.00	205	7.00			
Fa	70	2.39	275	9.39			
Gd	1160	39.59	1435	48.98			
Po	1	0.03	1436	49.01			
TΔ	1494	50.00	2030	100.00			

BldgType	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1Fam	2425	82.76	2425	82.76
2fmCon	62	2.12	2487	84.88
Duplex	109	3.72	2596	88.60
Twnhs	101	3.45	2697	92.05
TwnhsE	233	7.95	2930	100.00

CentralAir	Frequency	Percent	Cumulative Frequency	Cumulative Percent
N	196	6.69	196	6.69
Υ	2734	93.31	2930	100.00

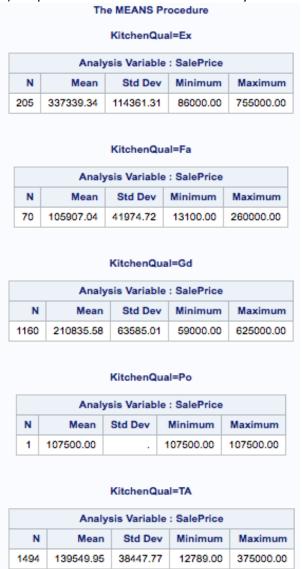
Histograms: KirchenQual (upper left), BldgType (upper right), CentralAir (bottom).



Conclusion: Three categorical variables were chosen to investigate: KitchenQual, BldgType and CentralAir. From the frequency analysis with KitchenQual, approximately 46% of the observations had kitchen quality that was Good/Excellent while 50% were typical. For BldgType most of the observations, 82%, were single-family homes, and similarly for CentralAir over 90% of homes had central air conditioning.

7. Relating categorical variables with the response

a) Output from PROC MEANS SalePrice by KitchenQual:



The average prices of homes with Good or Excellent KitchenQual were \$210,835 and \$337,339, respectively. Typical kitchen quality homes had an average sale price of \$139,549 while poor kitchen quality had a low sale price (\$107,500). Thus, KitchenQual is a reasonable indicator of sale price, although it might be a little subjective what makes a kitchen typical but not good.

b) Output from PROC MEANS SalePrice by BldgType:

The MEANS Procedure BldgType=1Fam Analysis Variable : SalePrice Ν Mean Std Dev Minimum Maximum 2425 184812.04 82821.80 12789.00 755000.00 BldgType=2fmCon Analysis Variable : SalePrice Ν Std Dev Maximum Mean Minimum 62 125581.71 31089.24 55000.00 228950.00 BldgType=Duplex Analysis Variable : SalePrice Std Dev Minimum Ν Mean Maximum 109 139808.94 39498.97 61500.00 269500.00 BldgType=Twnhs Analysis Variable: SalePrice Ν Mean Std Dev Minimum Maximum 101 135934.06 41938.93 73000.00 280750.00 BldgType=TwnhsE Analysis Variable : SalePrice Mean Std Dev Minimum Maximum 233 192311.91 66191.74 71000.00 392500.00

From the analysis in part 6, over 80% of the homes in the Ames data set are single-family homes, whose average sale price is \$184,812. Although townhouse inside units has a higher average sale price, \$192,311, they only represent approximately 8% of the BldgType in the Ames dataset. The cheaper homes are those, which are two-family conversions, duplexes or townhome end units, as they have lower average sale prices.

c) PROC MEANS saleprice by CentralAir

The MEANS Procedure							
		CentralAi	r=N				
Analysis Variable : SalePrice							
N Mean Std Dev Minimum Maximu							
196 101890.48 37597.02 12789.00 265979							
	Analy	CentralAi					
N	Analy:			Maximum			

As we saw from part 6, most of the Ames homes (>90%) have central air and as seen here these homes have a higher average sale price (\$186,452) compared to those without (101,890). Thus, CentralAir is a good indicator/co-indicator of sale price.

Conclusion: From the analysis of categorical variables in this section we know that KitchenQual, BldgType and CentralAir are good indicators of sale price, though they may not be entirely linear with respect to the sales price (see Section 8, EDA). These variables may also be grouped together, that is there may be multi-linearity evident. Thus, a single-family home with central air and a Good/Excellent kitchen quality will likely be at the higher end of the sales prices in Ames.

8. General EDA

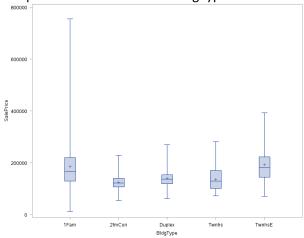
Used PROC MEANS for 10 chosen variables to display some general attributes of average homes in the Ames, IA area.

The MEANS Procedure							
Variable	N	Mean	Std Dev	Minimum	Maximum		
TotalFirSF	2930	1495.01	503.1301623	334.0000000	5642.00		
GrLivArea	2930	1499.69	505.5088875	334.0000000	5642.00		
houseage	2930	36.4341297	30.2913574	-1.0000000	136.0000000		
FullBath	2930	1.5665529	0.5529406	0	4.0000000		
BedroomAbvGr	2930	2.8542662	0.8277311	0	8.0000000		
WoodDeckSF	2930	93.7518771	126.3615619	0	1424.00		
BsmtFinSF1	2929	442.6295664	455.5908391	0	5644.00		
OverallQual	2930	6.0948805	1.4110261	1.0000000	10.0000000		
GarageCars	2929	1.7668146	0.7605664	0	5.0000000		
SalePrice	2930	180796.06	79886.69	12789.00	755000.00		

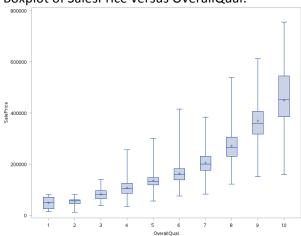
The means of some of these variables shown above provides some general indicators of the Ames house market. So on average an \$180,000 home in Ames may comprise an approximately 1500 sq. ft. total living area, with approx. 3 bedrooms and a 2-car garage and 1-2 full bathrooms.

Some boxplots of sales prices by BldgType, OverallQual and GarageCars were generated (see below). Interestingly, with OverallQual boxplot (overall quality of the home) although as the house quality gets better (10=Excellent, 1=Poor) the sale price increases.

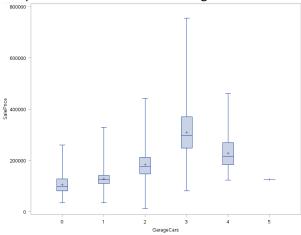
Boxplot of SalesPrice versus BldgType:



Boxplot of SalesPrice versus OverallQual:



Boxplot of SalesPrice versus GarageCars:



However, for most of the scoring categories (4-10), there is a high degree of variability, which increases with the score. This may be an indicator of the subjectivity with which these scores are attributed to each category of home. For OverallQual and GarageCars looking at the means, there is a non-linear relationship that is present.

Conclusion: Some of the EDA of the means of a number of the selected variables provides a snapshot of an average home in Ames, IA. As discussed in earlier sections some of variables when plotted versus sales price show some interesting and non-linear relationships with extensive variability, which needs to be noted for subsequent modeling analyses.

CONCLUSIONS

One of the aims of this initial assignment was to perform:

- a) Data Survey
- b) Data Quality Check
- c) Initial Exploratory Data Analysis (EDA)

As a result of this analysis we can conclude that the data present in this dataset allows us to draw some relationships between some of the numeric and categorical variables *versus* sale price of homes in Ames, IA. From the data survey and quality check we can state that most of the data surveyed in the Ames Housing dataset represents what they are designed to represent. Specifically, sale prices appear valid, although there are some errors in some variables (*e.g.* houseage with a -1 value) and some outliers exist. Twenty variables were chosen from prior knowledge and experience of house sales generally as potential predictors of sales price. Some of the EDA indicated that there are variables chosen that have a reasonable correlation with sales price, specifically: OverallQual, TotalFlrSF, GrLivArea, GarageCars, FullBath and houseage. There are also categorical variables such as KitchenQual, BldgType and GarageCars that can be used as candidate co-predictors of sale price.

As noted above although some predictors of sales price exist, the EDA analysis indicates that even for the best predictor variables (e.g. TotalFIrSF, GrLivArea) there is high degree of variability or scatter with increasing higher square footage and sales prices, for example. This is manifest with most, if not all, of the potential continuous and categorical predictors identified. This is a concern when trying to use a single predictor as a measure of sales price, as this can lead to a high error-rate in the prediction. In addition, although some of the relationships between predictor variables are linear (though with high scatter), others have curvi-linear relationships. This might suggest that further analysis with these predictors may require some transformation of the data from these variables. For example, some of the fan tailing (scatter) seen with TotalFIrSF/GrLivArea versus SalesPrice may be reduced with a logarithmic transformation to tighten up the distribution of points, leading to a better linear regression model.