410-57, Assignment #5 Anamitra Bhattacharyya

INTRODUCTION

This assignment specifically deals with building linear regression models (LRMs), using 'dummy' variables for use with their cognate categorical variables, and variable selection for model building. The overall goal of the assignment and project as a whole is to identify suitable predictors of house sale price in Ames, Iowa. The variables are derived from 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. Using a variety of automated variable selection procedures, in combination with assessment of the quality and significance of these models a more refined fitted model was development and tested using training and test data sets. This resulted in removal of some statistically insignificant variables and operational validation to assess the applicability of the model to develop a business policy relating to prediction of house prices in Ames, Iowa.

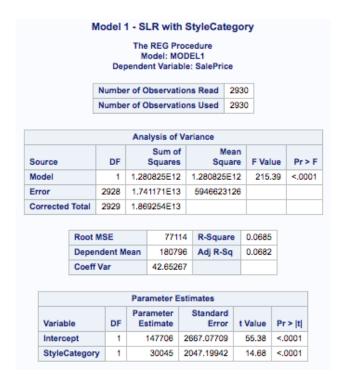
RESULTS

Part A: Dummy Coding of Categorical Variables

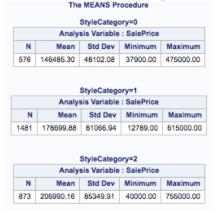
1. Categorical variable

Choosing HouseStyle as a categorical variable (but not using dummy variables) we generate an equation of the form (from the output table below):

y = 147706 (b0; intercept) + 30045(x) so the fitted y-hat values will be 147706 + 177751 (*i.e.* 147706+30045) + 207796 (*i.e.* 177751 +30045).



In a regression model the fitted model regression line should go through the mean values for x and y (see table below). However, these y-hat values (e.g. \$147,706, \$177,751, \$207,796) are not an exact match with the mean SalePrice (Y) values (e.g. \$146,485, \$176,699, \$206,990).



Conclusion: When not using dummy variables but assigning random numbers to the categorical variables, the y-hat fitted model does not pass through mean Y-values.

2. Using dummy variables

We need to fit appropriate dummy variables to the categorical variable chosen. When this is done we obtain the equation of the form (from the output table below):



y = 146485 + 32215*Style1 + 60505*Style2

The fitted model yhat values will be 146485, 178700, 206990; such that,

- a) when Style1=0 & Style2=0, then yhat=146485=intercept (baseline)
- b) when Style1=1 & Style2=0 then yhat = 146485 + 32215=178700;
- c) when Style1=0 & Style2=0 then yhat = 146485 + 60505 = 206990;

Coefficient of Style1 is 32215, which is the additional amount for a 1-story building on top of the 'baseline' price. The coefficient of Style2 is 60505, which is the additional amount for a 2-story building on top of the 'baseline' price.

Conclusion: These fitted values from this model with dummy variables are an exact match with the mean SalePrice (Y) values (e.g. \$146485, \$176,699, \$206,990) from the second table shown above. Thus, using dummy variables produces a y-hat model plane that passes through the mean Y values exactly.

3. Report on hypothesis tests for betas

The hypothesis being tested the overall (full model) regression models is:

H0: beta1 = beta2 = 0 H1: at least one beta \neq 0

The overall significance of this regression defined by the F-statistic is 107.91 and the p-value is < 0.0001, which is low. This result indicates to reject the null hypothesis for the full model suggesting that there is a correlation between SalePrice and HouseStyle.



Looking at the individual t-tests in the parameter table, the null hypotheses for the Style 1 and Style2 are:

a) H0: beta1 (Style1) = 0

H1: beta1 \neq 0

b) H0: beta2 (Style2) = 0

H1: beta2 \neq 0

Conclusion: Since the p-values for each of these t-tests in the parameter table above are low (< 0.0001), the null hypothesis is rejected and conditions satisfy the alternate hypothesis in each case. Therefore, there is a correlation between house style (Style1 and Style2) and SalePrice response variable.

4. Other categorical variable

Added a Zoning categorical variable, the summary table of which is shown below:

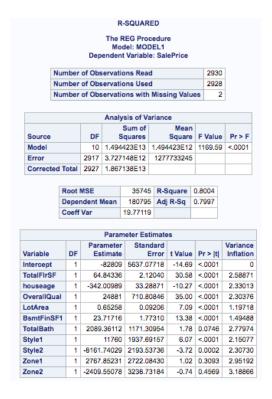


Part B: Automated variable selection

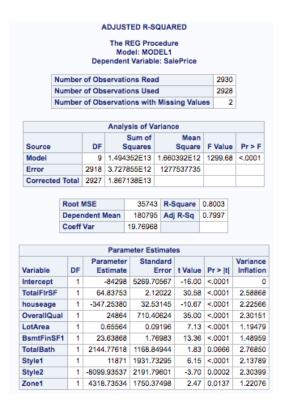
5. Alternate methods of variable selection

Six different methods of variable selection were chosen from a data set of variables comprising: TotalFlrSF, houseage, OverallQual, LotArea, BsmtFinSF1, TotalBath, HouseStyle and Zoning. The six variable selection methods comprised, R-Squared, adjusted R-Squared, Mallow's Cp, forward, backward and Stepwise. The results from the variable selection methods are shown below:

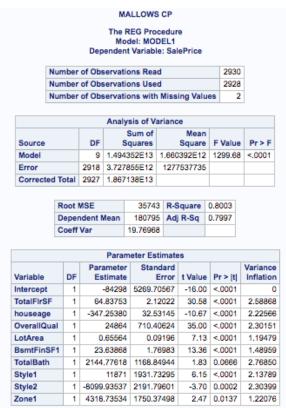
a) R-squared



b) Adjusted R-squared



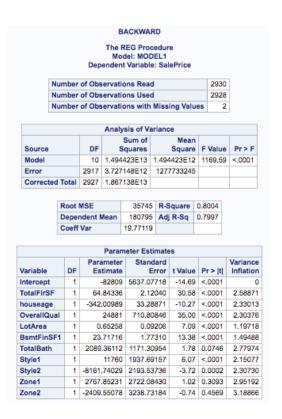
c) Mallow's Cp



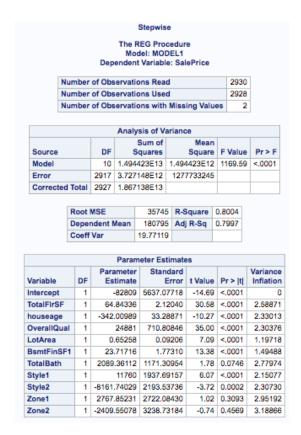
d) Forward

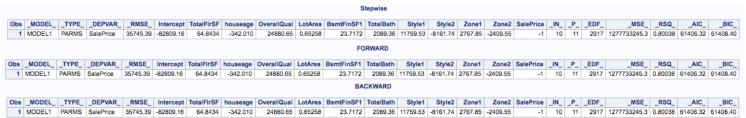
				FORWA	RD				
			The	REG Pro	cedur	ne.			
				del: MO					
		Dep	enden	t Variabl	e: Sa	lePrice			
1	Numbe	r of Obs	ervati	ons Rea	d			2930	
1	Number	r of Obs	ervati	ons Use	d			2928	3
1	Number	of Obs	ervati	ons with	Miss	ing Valu	es	2	2
			Analy	ysis of V	ariano	ce			
				Sum of		Mean			
Source		DF		Squares		Square	_		
Model		10				4423E12		69.59	<.0001
Error		2917		148E12	127	7733245	-		
Correcte	d Total	2927	1.867	138E13					
		MSE		3574		Square	8.0		
		ndent l	Mean	18079		R-Sq	0.7	997	
	Coef	f Var		19.7711	9				
			_						
				neter Es	timate	98	_		
									Varianc
Variable	DF		ameter timate		dard Error	t Value	P	r > Iti	
Variable Intercept	DF	Es			Error	t Value		r > t	Inflatio
	1	Es	timate	5637.0	Error		<.		Inflatio
Intercept	1	Es	timate -82809	5637.0	7718	-14.69	<.	0001	Inflatio 2.5887
Intercept TotalFirSF	1 1	64 -342	timate -82809 .84336	5637.0 5 2.1 33.2	7718 2040 8871	-14.69 30.58	<. <.	0001	2.5887 2.3301
Intercept TotalFirSF houseage	1 1	64 -342	timate -82809 .84336 .00989	5637.0 5 2.1 33.2 710.8	7718 2040 8871	-14.69 30.58 -10.27	<. <.	0001 0001 0001	2.5887 2.3301 2.3037
Intercept TotalFirSF houseage OverallQu	1 1 1 al 1	64 -342	timate -82809 .84336 .00989 24881	5637.0 5 2.1 3 33.2 710.8 0.0	7718 2040 8871 0846	-14.69 30.58 -10.27 35.00	<. <. <. <. <. <. <. <. <. <. <. <. <. <	0001 0001 0001 0001	2.5887 2.3301 2.3037 1.1971
Intercept TotalFirSF houseage OverallQu LotArea	1 1 1 al 1	64 -342 0 23	timate -82809 .84336 .00989 24881 .65258	5637.0 5 2.1 33.2 710.8 0.0 5 1.7	7718 2040 8871 0846 9206 7310	-14.69 30.58 -10.27 35.00 7.09	<. <. <. <. <. <. <. <. <. <. <. <. <. <	0001 0001 0001 0001 0001	2.5887 2.3301 2.3037 1.1971 1.4948
Intercept TotalFirSF houseage OverallQu LotArea BsmtFinS	1 1 1 al 1 F1 1	64 -342 0 23 2089	timate -82809 .84336 .00989 .24881 .65258	5637.0 5637.0 5 2.1 710.8 0.0 5 1.7 1171.3	7718 2040 8871 0846 9206 7310 0954	-14.69 30.58 -10.27 35.00 7.09 13.38	<. <. <. <. <. <. <. <. <. <. <. <. <. <	0001 0001 0001 0001 0001	2.5887 2.3301 2.3037 1.1971 1.4948 2.7797
Intercept TotalFirSF houseage OverallQu LotArea BsmtFinS TotalBath	1 1 al 1 F1 1	64 -342 0 23 2089	timate -82809 -84336 -00989 -24881 -65258 -71716 -36112	5637.0 5 2.1 9 33.2 710.8 9 0.0 6 1.7 1171.3 1937.6	7718 2040 8871 0846 9206 7310 0954 9157	-14.69 30.58 -10.27 35.00 7.09 13.38 1.78	<. <. <. <. <. <. <. <. <. <. <. <. <. <	0001 0001 0001 0001 0001 0001 0746	2.5887 2.3301 2.3037 1.1971 1.4948 2.7797 2.1507
Intercept TotalFIrSF houseage OverallQu LotArea BsmtFinS TotalBath Style1	1 1 al 1 F1 1 1	64 -342 0 23 2089	timate -82809 -84336 -00989 -24881 -65258 -71716 -36112 -11760	5637.0 5637.0 52.1 710.8 0.0 51.7 1171.3 1937.6 2193.5	7718 2040 8871 0846 9206 7310 0954 9157 3736	-14.69 30.58 -10.27 35.00 7.09 13.38 1.78 6.07	<. <. <. <. <. <. <. <. <. <. <. <. <. <	0001 0001 0001 0001 0001 0001 0746 0001	2.5887 2.3301 2.3037 1.1971 1.4948 2.7797 2.1507

e) Backward



f) Stepwise

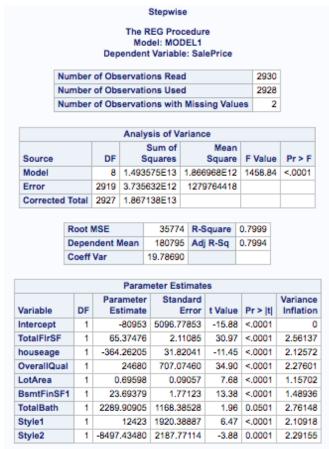




Conclusions: Overall the six different variable selection methods gave the same model results in terms of the summary table and p-values. P-values for the predictor variables in the selection models were all significant except for Zoning. Using MSE, AIC and BIC criteria to evaluate the selection methods, these gave the same results (see above). Thus, the Zoning variables appear to be candidates for removal from the model.

6. Tweaking variable selection model

Since zoning was not statistically significant, this was variable was deleted from the set and the model was re-fit using the stepwise selection method. The results from the analysis are shown below:



										Stepwise											
Obs	_MODEL_	_TYPE_	_DEPVAR_	_RMSE_	Intercept	TotalFirSF	houseage	OverallQual	LotArea	BsmtFinSF1	TotalBath	Style1	Style2	SalePrice	_IN_	_P_	_EDF_	_MSE_	_RSQ_	_AIC_	_BIC_
- 1	MODEL1	PARMS	SalePrice	35773.80	-80952.73	65.3748	-364.262	24679.60	0.69598	23.6938	2289.91	12423.44	-8497.43	-1	8	9	2919	1279764417.8	0.79993	61408.98	61411.03

Conclusion: Deleting the Zoning variable and re-fitting the model resulted in a small decrease in the adjusted R-squared for the overall regression model, 0.7994 compared 0.7997. However, the other variables selected in the model were all significant based on the p-values of their respective t-tests, including the 'HouseStyle' categorical variable.

Part C: Validation Framework

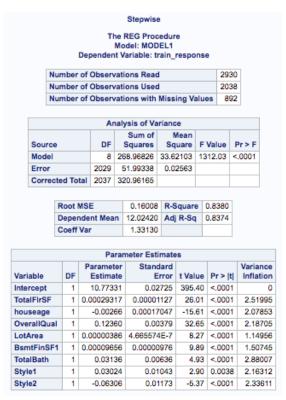
7. Create Training Set

Created a train/test split of the data for cross validation purposes in a 70%/30% ratio.

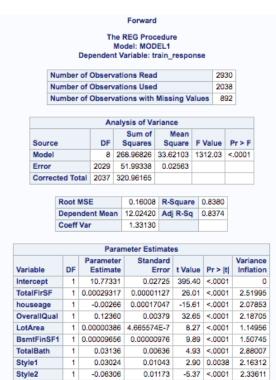
8. Model Identification by Automated Variable Selection and Predictive Accuracy

The response variable 'train_response' comprising the LogSalePrice and 70% training set, were used to execute the variable validation regimen from step 5 above. This was performed to find the 'best' models using automated variable selection using the techniques: adjusted R-Squared, AIC, Mallow's Cp, forward, backwards, and stepwise variable selection. The summary tables from each variable selection technique are reported below.

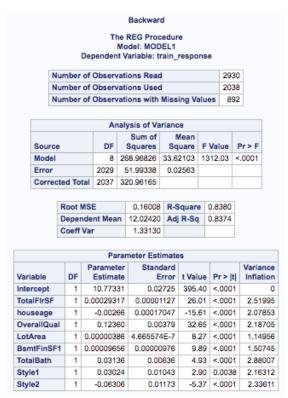
a) Stepwise



b) Forward



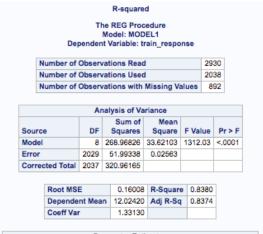
c) Backward



d) Adjusted R-squared

				A	dju	sted R-so	quare	d					
				T	he	REG Proc	edur	e					
						del: MOD							
			De	pender	it v	/ariable: t	rain_	respo	nse				
	N	umbe	r of	Observ	vati	ions Read	i			293	30		
	N	umbe	r of	Observ	vati	ions Used	i			203	38		
	N	umbe	r of	Observ	/ati	ions with	Miss	ing Va	lues	89	92		
				A	nal	ysis of Va		e Mean					
	Source	е		DF		Sum of Squares		uare	F Va	lue	Pr	> F	
	Model			8	26	88.96826	33.6	2103	1312	.03	<.0	001	
	Error			2029		51.99338	0.0	2563					
	Correc	ted T	otal	2037	32	20.96165							
											,		
		Root				0.16008		quare		380			
		Coef		nt Mea	n	1.33130	_	R-Sq	8.0	374			
		Coet	rvai			1.33130							
				Pa	rar	neter Est	imate	98					
			P	aramet	ter	Stan	dard				١	Varia	nce
Vari	able	DF		Estima	ite	E	rror	t Val	ue P	r > 1	t	Inflat	tion
	rcept	1	-	10.773		0.0.	2725	395.		.000	•		0
	alFirSF	1		000293		0.0000		26.0		.000		2.51	
	seage rallQua	1 1	-	-0.002			7047	-15.		000.		2.07	
	raliQua Area	1 1	-	0.123						.000		1.14	
	ntFinSF			000096		0.00000				.000	-	1.50	
	alBath	1	0.0	0.031			0636			.000		2.88	
Styl		1		0.030			1043			.003	•	2.16	
Styl		1		-0.063	06	0.0	1173	-5.3	37 <	.000	1	2.33	611

e) R-squared



		Paran	neter Estimate	s		
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Variance Inflation
Intercept	1	10.77331	0.02725	395.40	<.0001	0
TotalFirSF	1	0.00029317	0.00001127	26.01	<.0001	2.51995
houseage	1	-0.00266	0.00017047	-15.61	<.0001	2.07853
OverallQual	1	0.12360	0.00379	32.65	<.0001	2.18705
LotArea	1	0.00000386	4.665574E-7	8.27	<.0001	1.14956
BsmtFinSF1	1	0.00009656	0.00000976	9.89	<.0001	1.50745
TotalBath	1	0.03136	0.00636	4.93	<.0001	2.88007
Style1	1	0.03024	0.01043	2.90	0.0038	2.16312
Style2	1	-0.06306	0.01173	-5.37	<.0001	2.33611

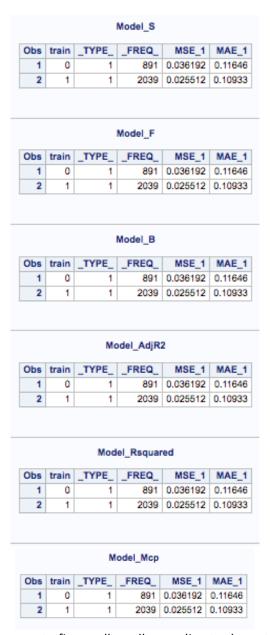
f) Mallow's Cp



Conclusions: The results from this step versus step 5, indicate the models are very similar to each other, in part because we have removed a non-significant variable – Zoning, in the starting

model. From the t-tables we can see from the p-values that they are all significant in the model as the p-values are small.

9.



Conclusion: All the models seem to fit equally well according to the output shown above. To evaluate the best model we need to find the one with for example, small values of MSE. The insample set (train=1) seemed to display the smallest value (MSE=0.025512 in-sample versus MSE=0.03612 for out-of-sample).

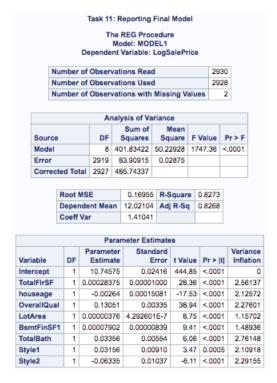
10. Operational Validation:

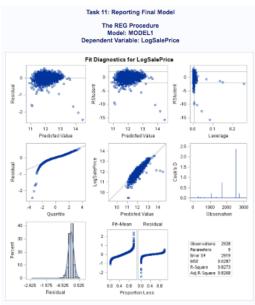
The criteria for evaluating these models, specifically MSE and MAE, do not translate easily to the development of business policy. A set of prediction grades was established: Grade 1 (best, within 10% of actual value), Grade 2 (medium, within 15% of actual value), and Grade 3 (worst), to provide a means of assessing predictive accuracy. Comparing the training (train=1) and test (train=0) sets in the output tables below, shows that there is a reasonable match between training and test sets. For example, for training set Grade 1 the percent frequency is 59.74% compared to 59.37% in the Grade 1 test set, which is close though slightly higher. There are comparable alignments between Grades 2 and 3 for the training and test sets.

	The FRE	Q Procedu	ıre	
	tr	rain=0		
Prediction_Grade	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Grade 1	529	59.37	529	59.37
Grade 2	155	17.40	684	76.77
Grade 3	207	23.23	891	100.00
Ste	pwise model			
Ste	The FRE	Q Procedu		
Ste	The FRE		ıre	Constitution
Ste	The FRE	Q Procedu		- Carrianative
Prediction_Grade	The FRE	Q Procedo	Cumulative	Percent
	The FRE	Q Procedurain=1	Cumulative Frequency	Cumulative Percent 59.74 76.46

Conclusion: Using this approach to assess predictive accuracy, we find that the percent of observations in each quality grade of the prediction is similar between training and test sets. This suggests a reasonable regression model has been created for the purposes of making reasonable business decisions.

11. Reporting final model





Conclusion: All the continuous variables picked out by the automated variable selection process were included in the final model and were statistically significant. While one of the categorical variables, Zoning, was dropped earlier in the process (step 6) since it was not statistically significant, another (e.g. 'HouseStyle') remained in the final model. Although the final model was derived from various variable selection procedures, and produced a reasonable correlation between training and test sets, there still remains some goodness-of-fit issues with the regression model.

CONCLUSIONS

After working on this problem and this data for several weeks, what are the challenges presented by the data? What are your recommendations for improving predictive accuracy?

Although the statistical significance of the final regression model was good (overall F-statistic), and the inclusion of the chosen regressor variables in the model was sound (based on the individual t-tests), there remain some concerns. First, from the goodness-of-fit metrics shown in the final model shown above, it is apparent that the randomness of the residuals in the plot above (top left) is in some question – some reverse funnel shape observed. Second, this final model from the assignment does not have SalePrice outliers removed from the earlier assignments. Thus, with the removal of further outliers it is likely that further improvement in the disposition of the residuals, GOF and adjusted-R-squared will be observed. Finally, pruning of the some of the outliers for each of the regressor variables chosen in the final model to will lead to further improvements in the final model, in combination with a transformation of the SalePrice response variable. These comments suggest that the model can be improved further. That said the 'best' regression model shown above has an adjusted-R-squared value >82% indicating that more than 82% of the variance in the SalePrice is explained by the regressor variables in the model.