Assignment #6
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Introduction:

A weakness in regression analysis is the tendency to build models that over-fit the data. Cross validation is a technique that splits the data and allows one to test the regression model on data that has not been associated with building the model. In this assignment, cross-validation will be utilized to assess the best multiple variable logistic regression model. Techniques such as backward selection, assessing goodness-of-fit, lift charts, and the KS test statistic all aid in selecting the best model.

In-Sample Results:

Throughout this assignment, two models will be compared. The first model is chosen based on management's decision and will be called Model 1. The second model, Model 2, is based on a statistical technique that analyzes all the variables in the model and chooses the best variables based on a p-value set at the user's desire, which is .05 for this exercise. The data being used to formulate the models are comprised of 70% of the total data. The output from running this procedure can be seen below.

Summary of Backward Elimination

Step	Effect Removed	DF	Number In	Wald Chi-Square	Pr > ChiSq
1	A8	1	16	0.0011	0.9733
2	A6_q	1	15	0.0427	0.8364
3	A7_h	1	14	0.1323	0.7161
4	A3	1	13	0.3335	0.5636
5	A10_t	1	12	0.3828	0.5361
6	A7_v	1	11	0.4865	0.4855
7	A6_k	1	10	0.6272	0.4284
8	A1_a	1	9	0.8127	0.3673
9	A7_bb	1	8	1.0080	0.3154
10	A6_w	1	7	1.9597	0.1616
11	A12_t	1	6	1.6777	0.1952
12	A2	1	5	1.9496	0.1626

Analysis of Maximum Likelihood Estimates Variables that are staying the model.

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-4.0846	0.5365	57.9692	<.0001
A11	1	0.2291	0.0680	11.3368	0.0008
A15	1	0.000597	0.000224	7.1232	0.0076
A4_u	1	0.8924	0.4054	4.8450	0.0277
A7_ff	1	-2.1065	0.9038	5.4325	0.0198
A9_t	1	4.0210	0.4378	84.3549	<.0001

From the results above, it can be seen that five variables had a p-value less than .05, and as a result will be the variables in the second model. From the past EDA in assignment five, I chose A11 as my optimal model and seeing that A11 and A9_t are both in this model my conclusion is that this model will be very strong.

The next step in assessing the two models is to compare the inferential statistics between the two models. Below is the "Model Fit Statistic".

Model Fit Statistics Model 1

Criterion	Intercept Only	Intercept and Covariates
AIC	620.703	340.739
SC	624.812	357.176
-2 Log L	618.703	332.739

Model Fit Statistics Model 2

Criterion	Intercept Only	Intercept and Covariates
AIC	620.703	289.616
SC	624.812	314.271
-2 Log L	618.703	277.616

This output compares how well the models fit the data. A high -2 Log L value equates to a worse fit. It is assumed that Model 2 will fit better given the fact it has higher covariates, but the AIC and SC penalize a model for having more covariates. Interestingly, Model 2 has a lower value for each criterion than Model 1. The Global Null hypothesis tests that all the explanatory variables have coefficients equal to zero. It can be seen that both variables have at least one coefficient that does not equal zero. Both models also have a significant p-value. Model 2 has much higher scores, and its coefficients are likely to be more form fitting on the data. This could lead to over-fitting which will be analyzed later.

Model 1 Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	285.9640	3	<.0001
Score	246.5494	3	<.0001
Wald	151.7473	3	<.0001

Model 2 Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Square**	**DF**	**Pr > ChiSq**
Likelihood Ratio	341.0870	5	<.0001
Score	267.3283	5	<.0001
Wald	131.5481	5	<.0001

The maximum likelihood analysis pared with the odds ratio estimates reveal statistically significant individual coefficients and their prospective magnitudes. In Model 1, A2 and A3 lack the statistical significance at the .05 threshold, and I would alert this point to management. Model 2 only has one variable that is not statistically significant, but it is rather close to the .05 threshold. In order to better understand the magnitude of the coefficients, interpreting the odds ratio is helpful. The odds ratio of a coefficient communicates that the predicted odds for that coefficient are the Point Estimate times the odds compared to that specific non-coefficient. For example, A9_t has 53 times the odds of non A9_t values of being 1. The magnitude for A9_t in model 1 is huge compared to Model 2. Also, A15 almost has a non-existent coefficient.

Model 1 Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-3.6287	0.5051	51.6051	<.0001
A9_t	1	3.9836	0.3302	145.5842	<.0001
A2	1	0.0227	0.0127	3.1641	0.0753
A3	1	0.0527	0.0314	2.8241	0.0929

Model 2 Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-3.5542	0.4514	61.9895	<.0001
A11	1	0.2229	0.0607	13.5025	0.0002
A15	1	0.000555	0.000207	7.1670	0.0074
A4_u	1	0.6854	0.3706	3.4200	0.0644
A7_ff	1	-2.1243	0.8686	5.9816	0.0145
A9_t	1	3.6107	0.3630	98.9523	<.0001

Model 1 Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Wald Confidence Limits**	
A9_t	53.712	28.122	102.590
A2	1.023	0.998	1.049
A3	1.054	0.991	1.121

Odds Ratio Estimates			
Effect	**Point Estimate**	**95% Wald Confidence Limits**	
A11	1.250	1.110	1.407
A15	1.001	1.000	1.001
A4_u	1.985	0.960	4.103
A7_ff	0.120	0.022	0.656
A9_t	36.992	18.161	75.349

The goodness-of-fit statistics include the percent concordant, percent discordant, Somer's D, Gamma, and Tau-a. The output for these statistics are listed below.

Model 1 Association of Predicted Probabilities and Observed Responses			
Percent Concordant	89.1	**Somers' D**	0.787
Percent Discordant	10.5	**Gamma**	0.790
Percent Tied	0.4	**Tau-a**	0.390
Pairs	50049	**c**	0.893

Model 2 Association of Predicted Probabilities and Observed Responses			
Percent Concordant	92.6	**Somers' D**	0.871
Percent Discordant	5.5	**Gamma**	0.888
Percent Tied	1.9	**Tau-a**	0.432
Pairs	50049	**c**	0.936

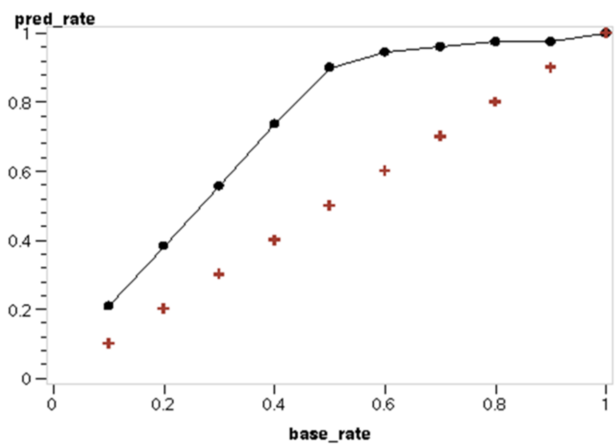
Both models have high percent concordant values. I look forward to analyzing this information on the test data. Model 2 is slightly better, and this comes as no surprise based on the prior analysis. For Model 1, the lift model reflects what is seen in the lift chart. When targeting 50% of the population, the lift is around 40%. For Model 2, the results are very similar, except the lift is 1 percent greater.

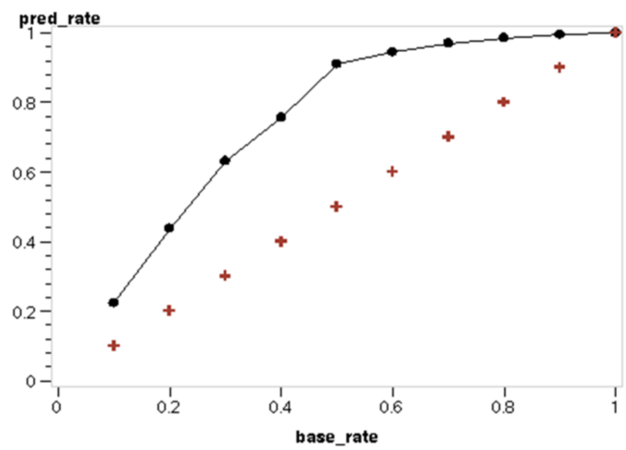
Model 1

Obs	score_decile	Y_Sum	Nobs	cum_obs	model_pred	pred_rate	base_rate	life
1	1	42	45	45	42	0.20896	0.1	0.10896
2	2	35	45	90	77	0.38308	0.2	0.18308
3	3	35	45	135	112	0.55721	0.3	0.25721
4	4	36	45	180	148	0.73632	0.4	0.33632
5	5	33	45	225	181	0.90050	0.5	0.40050
6	6	9	45	270	190	0.94527	0.6	0.34527
7	7	3	45	315	193	0.96020	0.7	0.26020
8	8	3	45	360	196	0.97512	0.8	0.17512
9	9	0	45	405	196	0.97512	0.9	0.07512
10	10	5	45	450	201	1.00000	1.0	0.00000

Model 2

Obs	score_decile	Y_Sum	Nobs	cum_obs	model_pred	pred_rate	base_rate	life
1	1	45	45	45	45	0.22388	0.1	0.12388
2	2	43	45	90	88	0.43781	0.2	0.23781
3	3	39	45	135	127	0.63184	0.3	0.33184
4	4	25	31	166	152	0.75622	0.4	0.35622
5	5	31	56	222	183	0.91045	0.5	0.41045
6	6	7	48	270	190	0.94527	0.6	0.34527
7	7	5	44	314	195	0.97015	0.7	0.27015
8	8	3	60	374	198	0.98507	0.8	0.18507
9	9	2	25	399	200	0.99502	0.9	0.09502
10	10	1	51	450	201	1.00000	1.0	0.00000

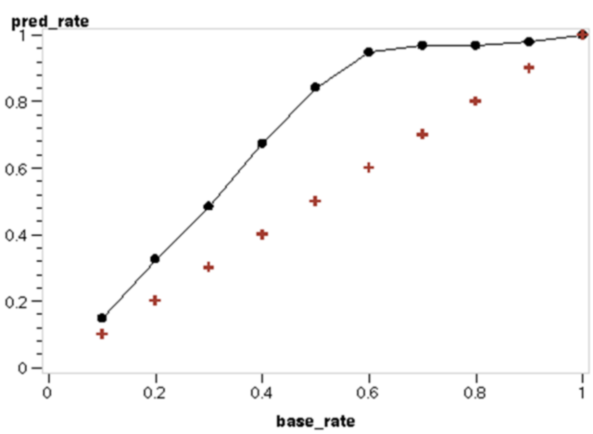


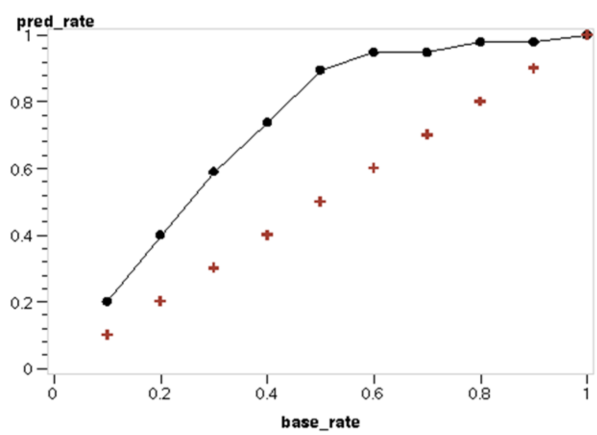


Interpreting the lift table and lift chart is key to understanding how the models perform on data that were not used to make the data. The red crosses on the graph represent a random guess, which lies at the 45 degree angle mark. For both models, the first five decile's are strongly predictive. Model 2 has stronger prediction. In my opinion, both models peak around 50% and have an optimum added lift of 39% percent for Model 2, and 34% for Model 1. Both models perform very similarly to their "in-sample" models, which leads me to believe that neither models are over fit. The Kolmogorov-Smirnov (KS) test is the same as the lift for the models. But, the importance of the KS test lies in its statistical validation between the two models. While I can see that the distributions are different, I need to statistically verify that they are different. For model 2, I multiplied the lift times the square root of (23*15/ (23+15) which equals 1.517 and rejects the null hypothesis that the distributions are the same. I would recommend to management to use Model 2, but I would want to know more about Model 1 and the significance of the variables. Perhaps after better understanding the variables, I would make an additional model with variables from both models.

Model 1								
Obs	**score_decile**	**Y_Sum**	**Nobs**	**cum_obs**	**model_pred**	**pred_rate**	**base_rate**	**Lift**
1	1	14	20	20	14	0.14737	0.1	0.04737
2	2	17	20	40	31	0.32632	0.2	0.12632
3	3	15	21	61	46	0.48421	0.3	0.18421
4	4	18	20	81	64	0.67368	0.4	0.27368
5	5	16	20	101	80	0.84211	0.5	0.34211
6	6	10	21	122	90	0.94737	0.6	0.34737
7	7	2	20	142	92	0.96842	0.7	0.26842
8	8	0	21	163	92	0.96842	0.8	0.16842
9	9	1	20	183	93	0.97895	0.9	0.07895
10	10	2	20	203	95	1.00000	1.0	0.00000

Model 2								
Obs	**score_decile**	**Y_Sum**	**Nobs**	**cum_obs**	**model_pred**	**pred_rate**	**base_rate**	**Lift**
1	1	19	20	20	19	0.20000	0.1	0.10000
2	2	19	20	40	38	0.40000	0.2	0.20000
3	3	18	21	61	56	0.58947	0.3	0.28947
4	4	14	17	78	70	0.73684	0.4	0.33684
5	5	15	23	101	85	0.89474	0.5	0.39474
6	6	5	21	122	90	0.94737	0.6	0.34737
7	7	0	16	138	90	0.94737	0.7	0.24737
8	8	3	32	170	93	0.97895	0.8	0.17895
9	9	0	12	182	93	0.97895	0.9	0.07895
10	10	2	21	203	95	1.00000	1.0	0.00000





Conclusion:

This assignment demonstrated how to split data and utilize cross-validation as a technique to hone the predictive modeling process. The code for this assignment was the most complex to date, and while interpreting the results I felt underwater. The new techniques learned in this assignment are very applicable, but I need much more practice before I remotely feel competent.

SAS Code:

```
*Daniel Prusinski Assignment 6 Version 1********************
*Lift Chart For Training A11 A15 A4_u A7_ff A9_t************
************************************************************;

*****Statement to access where the data is stored*****;
libname mydata '/courses/u_northwestern.edu1/i_833463/c_3505/SAS_Data/';
ods graphics on;

*****This creates the response variable*****;
data temp;
      set mydata.credit_approval;

      u=uniform(123);
      if (u<0.7) then train=1; else train=0;

      if (A16='+') then Y =1;
      else Y=0;

      if (train=1) then Y_train=Y; else Y_train=.;


      *****Categorical Variables*****
      *******************************
      *******************************;


if (A1='a') then A1_a=1; else A1_a=0;

if (A4='u') then A4_u=1; else A4_u=0;

if (A5='g') then A5_g=1; else A5_g=0;

if (A6='aa') then A6_aa=1; else A6_aa=0;
if (A6='c') then A6_c=1; else A6_c=0;
if (A6='cc') then A6_cc=1; else A6_cc=0;
if (A6='d') then A6_d=1; else A6_d=0;
if (A6='e') then A6_e=1; else A6_e=0;
if (A6='ff') then A6_ff=1; else A6_ff=0;
if (A6='i') then A6_i=1; else A6_i=0;
if (A6='j') then A6_j=1; else A6_j=0;
if (A6='k') then A6_k=1; else A6_k=0;
if (A6='m') then A6_m=1; else A6_m=0;
if (A6='q') then A6_q=1; else A6_q=0;
if (A6='r') then A6_r=1; else A6_r=0;
if (A6='w') then A6_w=1; else A6_w=0;

*****I left off a few of the small variables, I want to see what this
does*****;
if (A7='bb') then A7_bb=1; else A7_bb=0;
if (A7='ff') then A7_ff=1; else A7_ff=0;
if (A7='h') then A7_h=1; else A7_h=0;
if (A7='v') then A7_v=1; else A7_v=0;

if (A9='t') then A9_t=1; else A9_t=0;

if (A10='t') then A10_t=1; else A10_t=0;
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```
if (A12='t') then A12_t=1; else A12_t=0;

if (A13='g') then A13_g=1; else A13=_g=0;

*****This purges the Data, 90 LSB*****;
      if A1 = '?' then delete;
      else if A2 = '.' then delete;
      else if A3 = '.' then delete;
      else if A4 = '?' then delete;
      else if A5 = '?' then delete;
      else if A6 = '?' then delete;
      else if A7 = '?' then delete;
      else if A8 = '.' then delete;
      else if A9 = '?' then delete;
      else if A10 = '?' then delete;
      else if A11 = '.' then delete;
      else if A12 = '?' then delete;
      else if A13 = '?' then delete;
      else if A14 = '.' then delete;
      else if A15 = '.' then delete;
run;


proc logistic data=temp descending;
model Y_train = A2 A3 A8 A11 A15
      A1_a A4_u A5_g A6_k A6_q A6_w A7_bb A7_ff A7_h A7_v
      A9_t A10_t A12_t A13_g / selection=backward;
output out=model_data pred=yhat;
run;



****************************************
****************************************
****************************************
This is the beginning of building the
lift chart for A11 A15 A4_u A7_ff A9_t*********;

proc logistic data=temp descending;
model Y_train = A11 A15 A4_u A7_ff A9_t;
output out=model_data2 pred=yhat;
run;

proc npar1way date=temp;
class Y;
var A11, A15;
run


proc rank data=model_data2
out=training_scores descending groups=10;
var yhat;
ranks score_decile;
where train=1;
run;
```

```
*****This creates the lift chart*****;
proc means data=training_scores sum;
class score_decile;
var Y;
output out=pm_out sum(Y)=Y_Sum;
run;

proc print data=pm_out;
run;

data lift_chart;
      set pm_out (where=(_type_=1));
      by _type_;
      Nobs=_freq_;
      score_decile = score_decile+1;

      if first._type_ then do;
            cum_obs=Nobs;
            model_pred=Y_Sum;
      end;
      else do;
            cum_obs=cum_obs+Nobs;
            model_pred=model_pred+Y_Sum;
      end;
      retain cum_obs model_pred;

***** 201 represents the number of successes
This value will need to be changed with different samples*****;

      pred_rate=model_pred/201;
      base_rate=score_decile*0.1;
      lift = pred_rate-base_rate;

      drop _freq_ _type_;
run;

proc print data=lift_chart;
run;

ods graphics on;
title 'In-Sample Lift Chart';
symbol1 color=red interprol=join value=dot height=1;
symbol2 color=black interpol=join value=dot height=1;
proc gplot data=lift_chart;
plot pred_rate*base_rate base_rate*base_rate / overlay;
run; quit;
ods graphics off;

****************************************
****************************************
This is the beginning of building the
lift chart for A11 A15 A4_u A7_ff A9_t*********;

proc logistic data=temp descending;
model Y_train = A11 A15 A4_u A7_ff A9_t;
output out=model_data pred=yhat;
run;
```

```
proc rank data=model_data
out=training_scores descending groups=10;
var yhat;
ranks score_decile;
where train=0;
run;

*****This creates the lift chart*****;
proc means data=training_scores sum;
class score_decile;
var Y;
output out=pm_out sum(Y)=Y_Sum;
run;

proc print data=pm_out;
run;

data lift_chart;
      set pm_out (where=(_type_=1));
      by _type_;
      Nobs=_freq_;
      score_decile = score_decile+1;

      if first._type_ then do;
            cum_obs=Nobs;
            model_pred=Y_Sum;
      end;
      else do;
            cum_obs=cum_obs+Nobs;
            model_pred=model_pred+Y_Sum;
      end;
      retain cum_obs model_pred;

***** 201 represents the number of successes
This value will need to be changed with different samples*****;

      pred_rate=model_pred/95;
      base_rate=score_decile*0.1;
      life = pred_rate-base_rate;

      drop _freq_ _type_;
run;

proc print data=lift_chart;
run;

ods graphics on;
title 'In-Sample Lift Chart';
symbol1 color=red interprol=join value=dot height=1;
symbol2 color=black interpol=join value=dot height=1;
proc gplot data=lift_chart;
plot pred_rate*base_rate base_rate*base_rate / overlay;
run; quit;
ods graphics off;

proc logistic data=temp descending;
```

```
model Y_train = A9_t A2 A3;
output out=model_data2 pred=yhat;
run;

proc rank data=model_data2
out=training_scores descending groups=10;
var yhat;
ranks score_decile;
where train=1;
run;

*****This creates the lift chart*****;
proc means data=training_scores sum;
class score_decile;
var Y;
output out=pm_out sum(Y)=Y_Sum;
run;

proc print data=pm_out;
run;

data lift_chart;
      set pm_out (where=(_type_=1));
      by _type_;
      Nobs=_freq_;
      score_decile = score_decile+1;

      if first._type_ then do;
            cum_obs=Nobs;
            model_pred=Y_Sum;
      end;
      else do;
            cum_obs=cum_obs+Nobs;
            model_pred=model_pred+Y_Sum;
      end;
      retain cum_obs model_pred;

***** 201 represents the number of successes
This value will need to be changed with different samples*****;

      pred_rate=model_pred/201;
      base_rate=score_decile*0.1;
      life = pred_rate-base_rate;

      drop _freq_ _type_;
run;

proc print data=lift_chart;
run;

ods graphics on;
title 'In-Sample Lift Chart';
symbol1 color=red interprol=join value=dot height=1;
symbol2 color=black interpol=join value=dot height=1;
proc gplot data=lift_chart;
plot pred_rate*base_rate base_rate*base_rate / overlay;
run; quit;
```

```
ods graphics off;

proc rank data=model_data2
out=testing_scores descending groups=10;
var yhat;
ranks score_decile;
where train=0;
run;

*****This creates the lift chart*****;
proc means data=testing_scores sum;
class score_decile;
var Y;
output out=pm_out sum(Y)=Y_Sum;
run;

proc print data=pm_out;
run;

data lift_chart;
      set pm_out (where=(_type_=1));
      by _type_;
      Nobs=_freq_;
      score_decile = score_decile+1;

      if first._type_ then do;
            cum_obs=Nobs;
            model_pred=Y_Sum;
      end;
      else do;
            cum_obs=cum_obs+Nobs;
            model_pred=model_pred+Y_Sum;
      end;
      retain cum_obs model_pred;

***** 201 represents the number of successes
This value will need to be changed with different samples*****;

      pred_rate=model_pred/95;
      base_rate=score_decile*0.1;
      life = pred_rate-base_rate;

      drop _freq_ _type_;
run;

proc print data=lift_chart;
run;

ods graphics on;
title 'Out-Of-Sample Lift Chart';
symbol1 color=red interprol=join value=dot height=1;
symbol2 color=black interpol=join value=dot height=1;
proc gplot data=lift_chart;
plot pred_rate*base_rate base_rate*base_rate / overlay;
run; quit;
```