Machine Learning Analytic

"Forward Logistic Regression" Results

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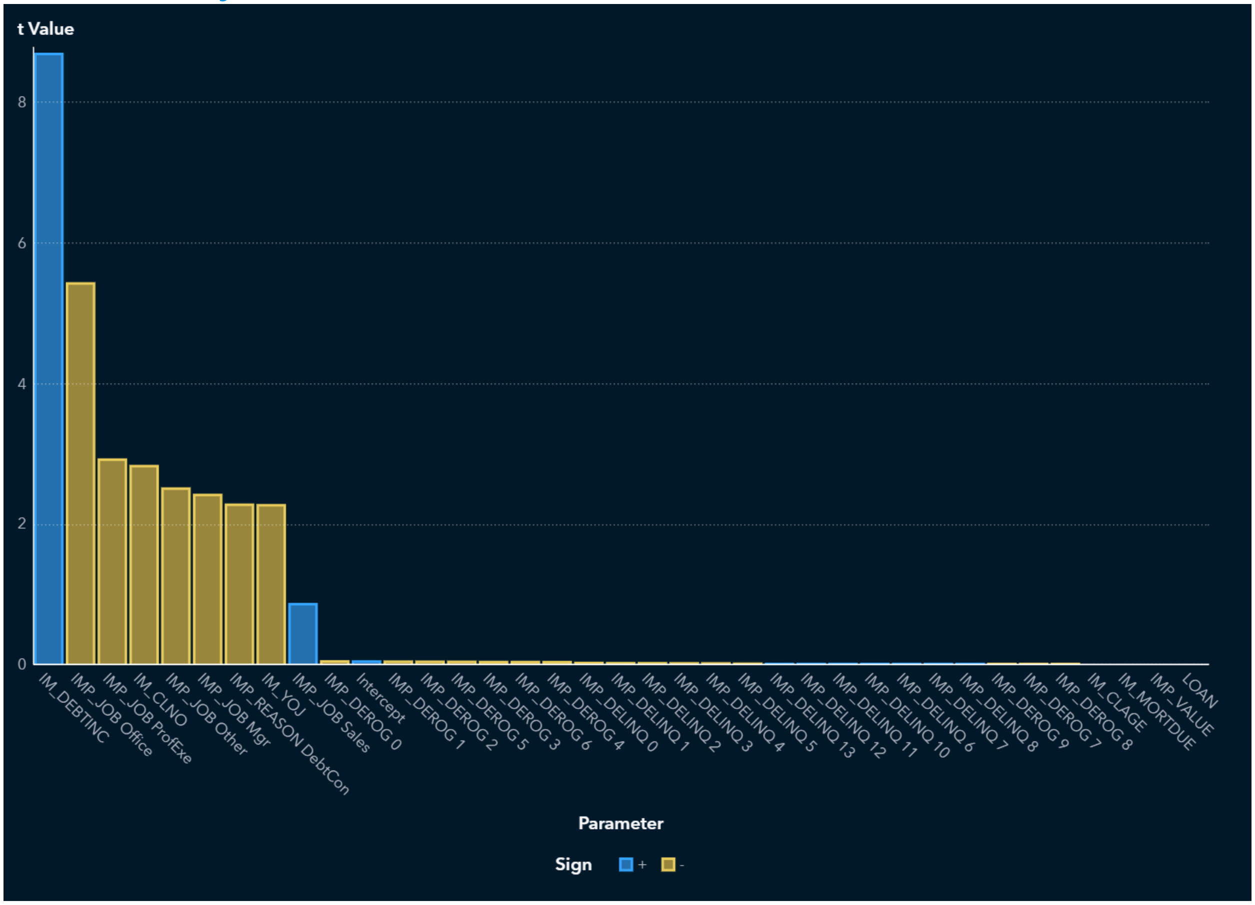
Contents

t Values by Parameter



This plot displays the absolute value of the t value for each parameter estimate in the logistic regression model. Larger values indicate more significant parameters. The bar that represents the parameter is colored by the sign of the estimate. Bars that are colored as positive (+) correspond to a positive parameter estimate, which indicates an increase in the predicted probability of the event as the parameter value increases. Bars that are colored as negative (-) correspond to a negative parameter estimate, which indicates a decrease in the predicted probability of event as the parameter value increases. The most significant parameter is IM_DEBTINC with a t value of 8.69.

Parameter Estimates

Effect	Parameter	t Value	Sign
IM_DEBTINC	IM_DEBTINC	8.6896	+
IMP_JOB	IMP_JOB Office	5.4274	-
IMP_JOB	IMP_JOB ProfExe	2.9225	-
IM_CLNO	IM_CLNO	2.8299	-
IMP_JOB	IMP_JOB Other	2.5110	-
IMP_JOB	IMP_JOB Mgr	2.4200	-
IMP_REASON	IMP_REASON DebtCon	2.2812	-
IM_YOJ	IM_YOJ	2.2738	-
IMP_JOB	IMP_JOB Sales	0.8675	+
IMP_DEROG	IMP_DEROG 0	0.0540	-
Intercept	Intercept	0.0525	+
IMP_DEROG	IMP_DEROG 1	0.0503	-
IMP_DEROG	IMP_DEROG 2	0.0489	-
IMP_DEROG	IMP_DEROG 5	0.0478	-
IMP_DEROG	IMP_DEROG 3	0.0447	-
IMP_DEROG	IMP_DEROG 6	0.0445	-
IMP_DEROG	IMP_DEROG 4	0.0436	-
IMP_DELINQ	IMP_DELINQ 0	0.0317	-
IMP_DELINQ	IMP_DELINQ 1	0.0286	-
IMP_DELINQ	IMP_DELINQ 2	0.0280	-
IMP_DELINQ	IMP_DELINQ 3	0.0265	-
IMP_DELINQ	IMP_DELINQ 4	0.0252	-
IMP_DELINQ	IMP_DELINQ 5	0.0211	-
IMP_DELINQ	IMP_DELINQ 13	0.0066	+
IMP_DELINQ	IMP_DELINQ 12	0.0057	+
IMP_DELINQ	IMP_DELINQ 11	0.0055	+
IMP_DELINQ	IMP_DELINQ 10	0.0040	+

Effect	Parameter	t Value	Sign
IMP_DELINQ	IMP_DELINQ 6	0.0037	+
IMP_DELINQ	IMP_DELINQ 7	0.0037	+
IMP_DELINQ	IMP_DELINQ 8	0.0034	+
IMP_DEROG	IMP_DEROG 9	0.0030	-
IMP_DEROG	IMP_DEROG 7	0.0022	-
IMP_DEROG	IMP_DEROG 8	0.0007	-
IM_CLAGE	IM_CLAGE		-
IM_MORTDUE	IM_MORTDUE		-
IMP_DELINQ	IMP_DELINQ 15		+
IMP_REASON	IMP_REASON HomeImp		+
IMP_JOB	IMP_JOB Self		+
IMP_VALUE	IMP_VALUE		+
LOAN	LOAN		-
IMP_DEROG	IMP_DEROG 10		+

Estimate	Absolute Estimate	Standard Error	Chi-Square
0.0528	0.0528	0.0061	75.5087
-1.1993	1.1993	0.2210	29.4563
-0.6074	0.6074	0.2078	8.5408
-0.0123	0.0123	0.0043	8.0086
-0.5030	0.5030	0.2003	6.3051
-0.5221	0.5221	0.2158	5.8565
-0.1913	0.1913	0.0839	5.2037
-0.0131	0.0131	0.0058	5.1703
0.2673	0.2673	0.3081	0.7526
-13.2509	13.2509	245.5029	0.0029
23.9428	23.9428	455.9524	0.0028
-12.3414	12.3414	245.5029	0.0025
-12.0118	12.0118	245.5029	0.0024

Estimate	Absolute Estimate	Standard Error	Chi-Square
-11.7260	11.7260	245.5036	0.0023
-10.9776	10.9776	245.5031	0.0020
-10.9348	10.9348	245.5036	0.0020
-10.6968	10.6968	245.5035	0.0019
-12.1916	12.1916	384.2147	0.0010
-10.9717	10.9717	384.2147	0.0008
-10.7441	10.7441	384.2147	0.0008
-10.1669	10.1669	384.2147	0.0007
-9.6882	9.6882	384.2148	0.0006
-8.1140	8.1140	384.2150	0.0004
3.5884	3.5884	543.3616	0.0000
3.0876	3.0876	543.3615	0.0000
2.5519	2.5519	462.0700	0.0000
1.8922	1.8922	469.0538	0.0000
1.4419	1.4419	389.1846	0.0000
1.4713	1.4713	397.1124	0.0000
1.4392	1.4392	420.3918	0.0000
-0.9455	0.9455	315.7249	0.0000
-0.5918	0.5918	265.1938	0.0000
-0.1994	0.1994	280.2879	0.0000
-0.0061	0.0061		
0.0000	0.0000		
0	0		
0	0		
0	0		
0.0000	0.0000		
0.0000	0.0000		
0	0		

Pr > Chi-Square	Degrees of Freedom
0.0000	1
0.0000	1
0.0035	1
0.0047	1
0.0120	1
0.0155	1
0.0225	1
0.0230	1
0.3856	1
0.9570	1
0.9581	1
0.9599	1
0.9610	1
0.9619	1
0.9643	1
0.9645	1
0.9652	1
0.9747	1
0.9772	1
0.9777	1
0.9789	1
0.9799	1
0.9832	1
0.9947	1
0.9955	1
0.9956	1
0.9968	1
0.9970	1

Pr > Chi-Square	Degrees of Freedom
0.9970	1
0.9973	1
0.9976	1
0.9982	1
0.9994	1
	0
	0
	0
	0
	0
	0
	0
	0

Selection Summary

Step	Effect Entered	Number of Effects	SBC
0	Intercept	1	5,965.1625
1	IMP_DELINQ	2	5,314.3655
2	IMP_DEROG	3	5,235.5867
3	IM_CLAGE	4	5,099.4411
4	IM_DEBTINC	5	4,996.3894
5	LOAN	6	4,980.1606
6	IMP_JOB	7	4,962.6008
7	IM_CLNO	8	4,950.7771
8	IMP_REASON	9	4,952.8749
9	IMP_VALUE	10	4,956.3960
10	IM_MORTDUE	11	4,949.1240
11	IM_YOJ	12	4,943.8914
12	IMP_NINQ	13	4,955.5952

Optimal SBC
0
0
0
0
0
0
0
0
0
0
0
1
0

Regression Fit Statistics

Statistic	Description	Value
M2LL	-2 Log Likelihood	4,656.9564
AIC	AIC (smaller is better)	4,722.9564
AICC	AICC (smaller is better)	4,723.3351
SBC	SBC (smaller is better)	4,943.8196

Score Inputs

Name	Role	Variable Level	Type
DELINQ	INPUT	NOMINAL	N
DEROG	INPUT	NOMINAL	N
IM_CLAGE	INPUT	INTERVAL	N
IM_CLNO	INPUT	INTERVAL	N
IM_DEBTINC	INPUT	INTERVAL	N
IM_MORTDUE	INPUT	INTERVAL	N
IM_YOJ	INPUT	INTERVAL	N
JOB	INPUT	NOMINAL	C
LOAN	INPUT	INTERVAL	N
NINQ	INPUT	NOMINAL	N
REASON	INPUT	BINARY	C
VALUE	INPUT	INTERVAL	N

Variable Type	Variable Label	Variable Format	Variable Length
double			8
double			8
double			8
double			8
double			8
double			8
double			8
char			7
double			8
double			8
char			7
double			8

Score Outputs

Name	Role	Type	Variable Type
EM_CLASSIFICATION	CLASSIFICATION	C	char
EM_EVENTPROBABILITY	PREDICT	N	double
EM_PROBABILITY	PREDICT	N	double
IMP_DELINQ	INPUT	N	double
IMP_DEROG	INPUT	N	double
IMP_JOB	INPUT	C	char
IMP_NINQ	INPUT	N	double
IMP_REASON	INPUT	C	char
IMP_VALUE	INPUT	N	double
I_BAD	CLASSIFICATION	C	char
P_BAD0	PREDICT	N	double
P_BAD1	PREDICT	N	double

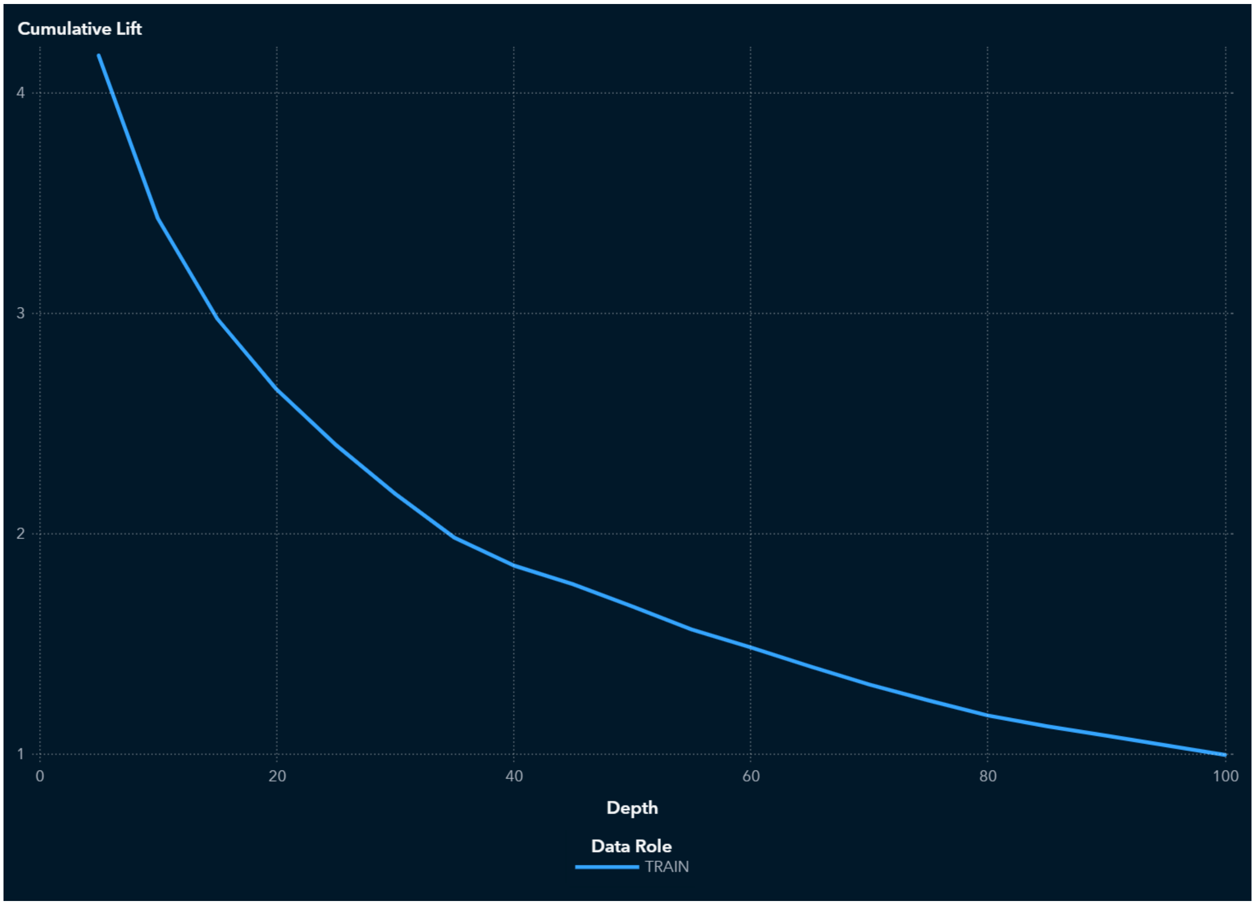
Variable Label	Variable Format	Variable Length	Creator
Predicted for BAD		12	logisticreg
Probability for BAD=1		8	logisticreg
Probability of Classification		8	logisticreg
Imputed DELINQ		8	impute
Imputed DEROG		8	impute
Imputed JOB		7	impute
Imputed NINQ		8	impute
Imputed REASON		7	impute
Imputed VALUE		8	impute
Into: BAD		12	logisticreg
Predicted: BAD=0		8	logisticreg

Variable Label	Variable Format	Variable Length	Creator
Predicted: BAD=1		8	logisticreg

Function	Creator GUID
CLASSIFICATION	73093e20-25d0-45e3-bc4c-42759840d7c6
PREDICT	73093e20-25d0-45e3-bc4c-42759840d7c6
PREDICT	73093e20-25d0-45e3-bc4c-42759840d7c6
TRANSFORM	b727c11b-1371-4c1d-8746-51b94c237069
TRANSFORM	b727c11b-1371-4c1d-8746-51b94c237069
TRANSFORM	b727c11b-1371-4c1d-8746-51b94c237069
TRANSFORM	b727c11b-1371-4c1d-8746-51b94c237069
TRANSFORM	b727c11b-1371-4c1d-8746-51b94c237069
TRANSFORM	b727c11b-1371-4c1d-8746-51b94c237069
CLASSIFICATION	73093e20-25d0-45e3-

Function	Creator GUID
	bc4c-42759840d7c6
PREDICT	73093e20-25d0-45e3-bc4c-42759840d7c6
PREDICT	73093e20-25d0-45e3-bc4c-42759840d7c6

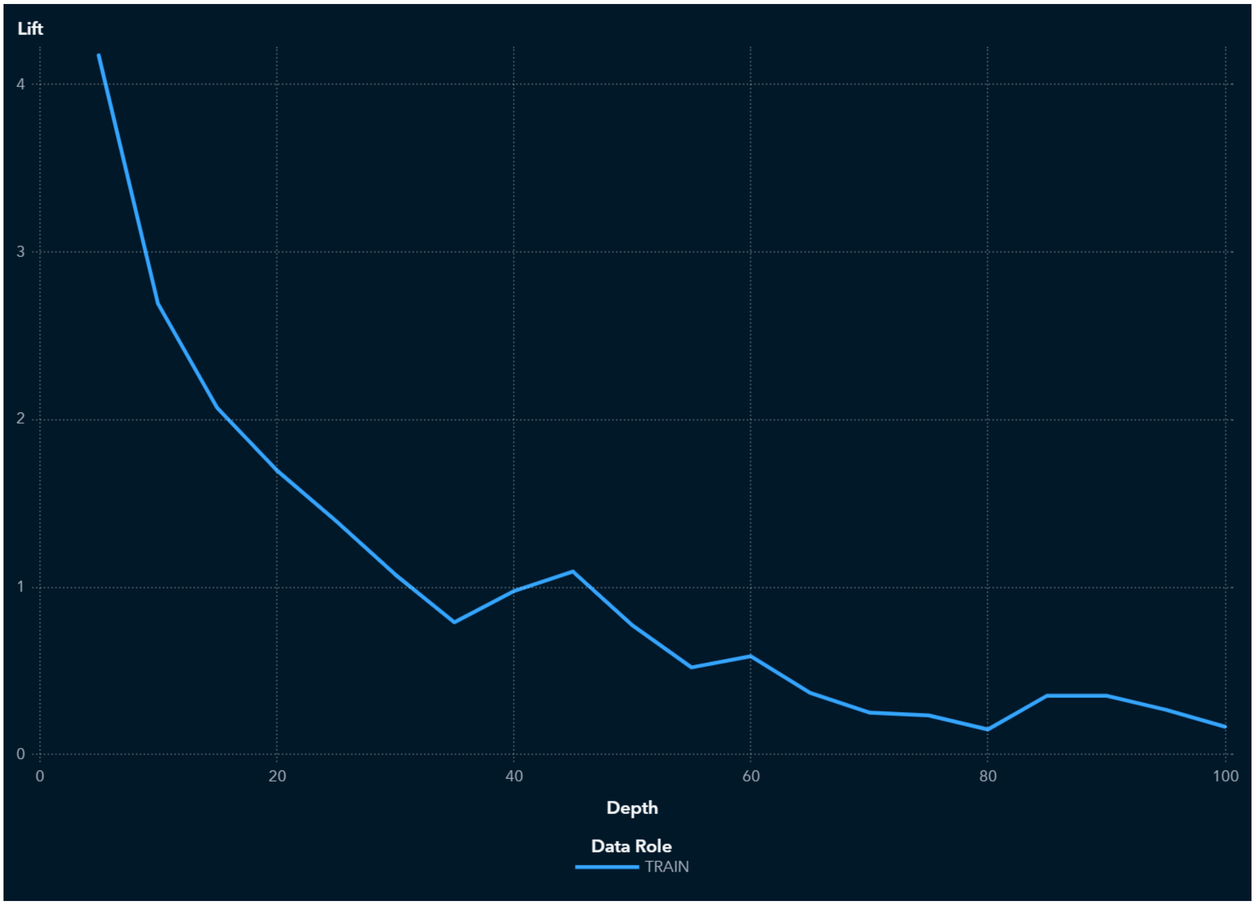
Cumulative Lift



The TRAIN partition has a Cumulative Lift of 3.43 in the 10% quantile (depth of 10) meaning there are 3.43 times more events in the first two quantiles than expected by random (10% of the total number of events). Because this value is greater than 1, it is better to use your model to identify responders than no model, based on the selected partition.

Cumulative lift is calculated by sorting each partition in descending order by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. The cumulative lift for a particular quantile is the ratio of the number of events across all quantiles up to and including the current quantile to the number of events that would be there at random, or equivalently, the ratio of the cumulative response percentage to the baseline response percentage. The cumulative lift at depth 10 includes the top 10% of the data, which is the first 2 quantiles, which would have 10% of the events at random. Thus, cumulative lift measures how much more likely it is to observe an event in the quantiles than by selecting observations at random.

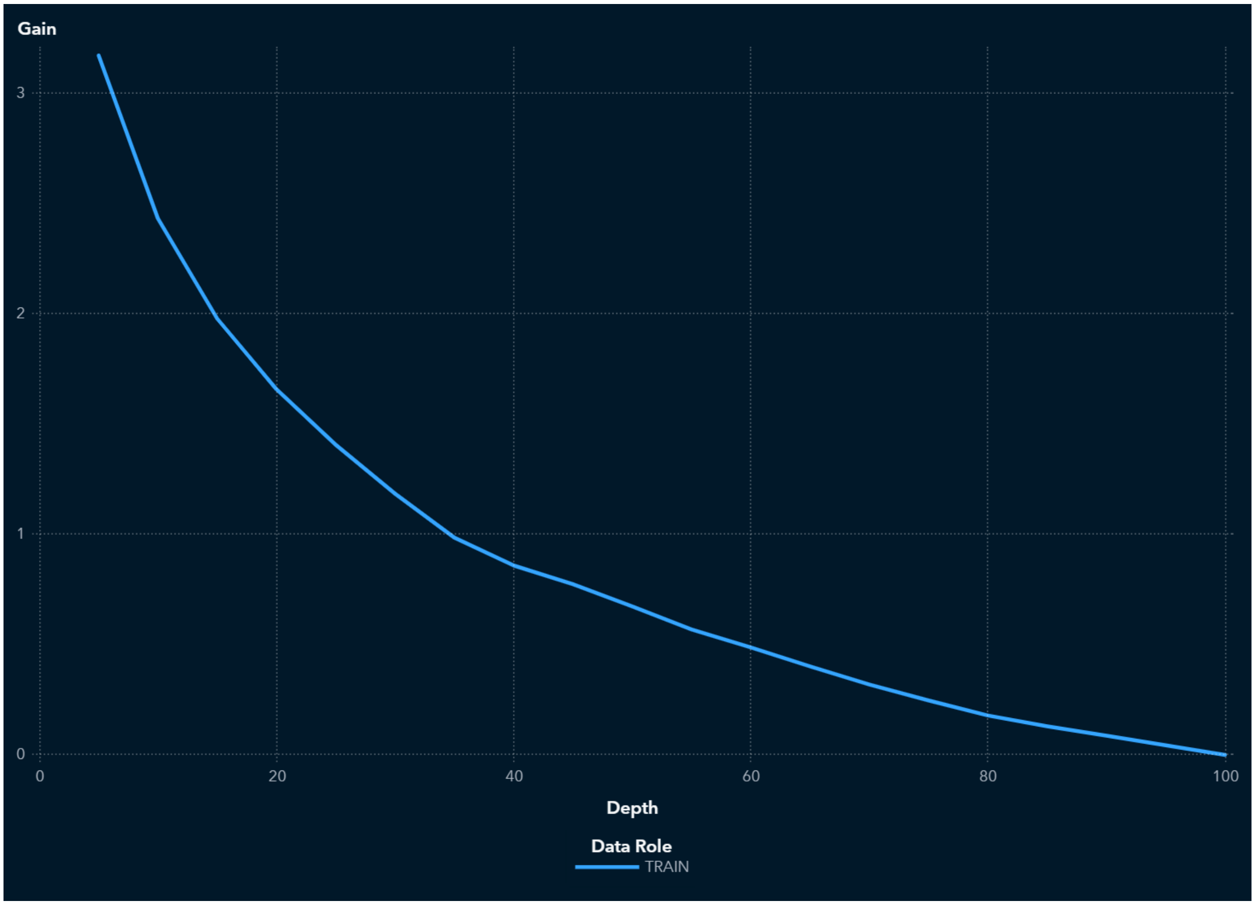
Lift



The TRAIN partition has a Lift of 4.17 in the 5% quantile (depth of 5) meaning there are 4.17 times more events in that quantile than expected by random (5% of the total number of events). Because this value is greater than 1, it is better to use your model to identify responders than no model, based on the selected partition.

Lift is calculated by sorting each partition in descending order by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. Lift is the ratio of the number of events in that quantile to the number of events that would be there at random, or equivalently, the ratio of the response percentage to the baseline response percentage. With 20 quantiles, it is expected that 5% of the events occur in each quantile. Thus, Lift measures how much more likely it is to observe an event in each quantile than by selecting observations at random.

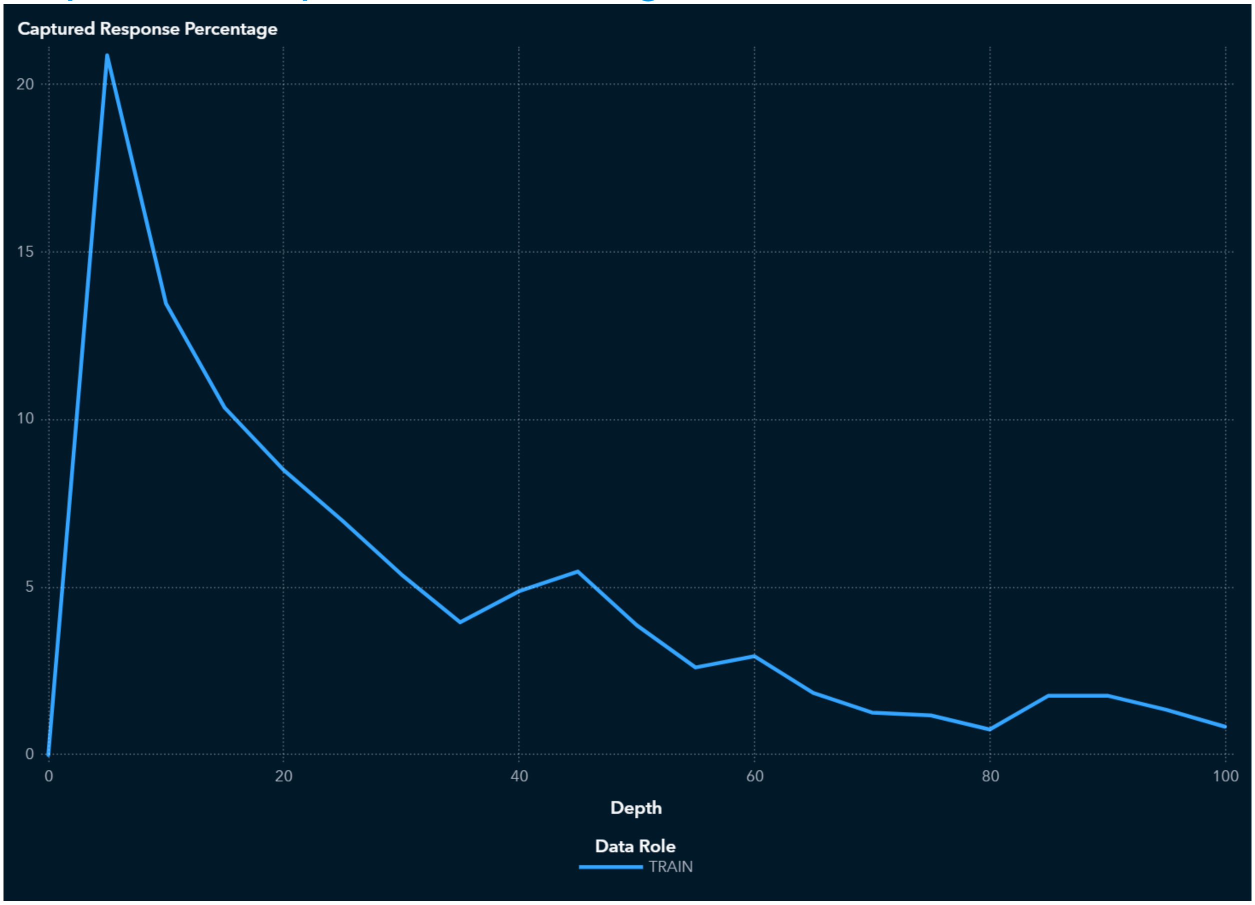
Gain



The TRAIN partition has a Gain of 2.4 at the 10% quantile (depth of 10). Because this value is greater than 0, it is better to use your model to identify responders than no model, based on the selected partition. The best possible value of Gain for this partition at depth 10 is 4.01.

Gain is calculated by sorting each partition in descending order by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. Gain is a cumulative measure for the quantiles up to an including the current one and is calculated as (number of events in the quantiles) / (number of events expected by random) - 1. With 20 quantiles, it is expected that 5% of the events occur in each quantile. Note that the value of Gain is the same as the value of Cumulative Lift - 1. If the value of Gain is greater than 0, then your model is better at identifying events than using no model.

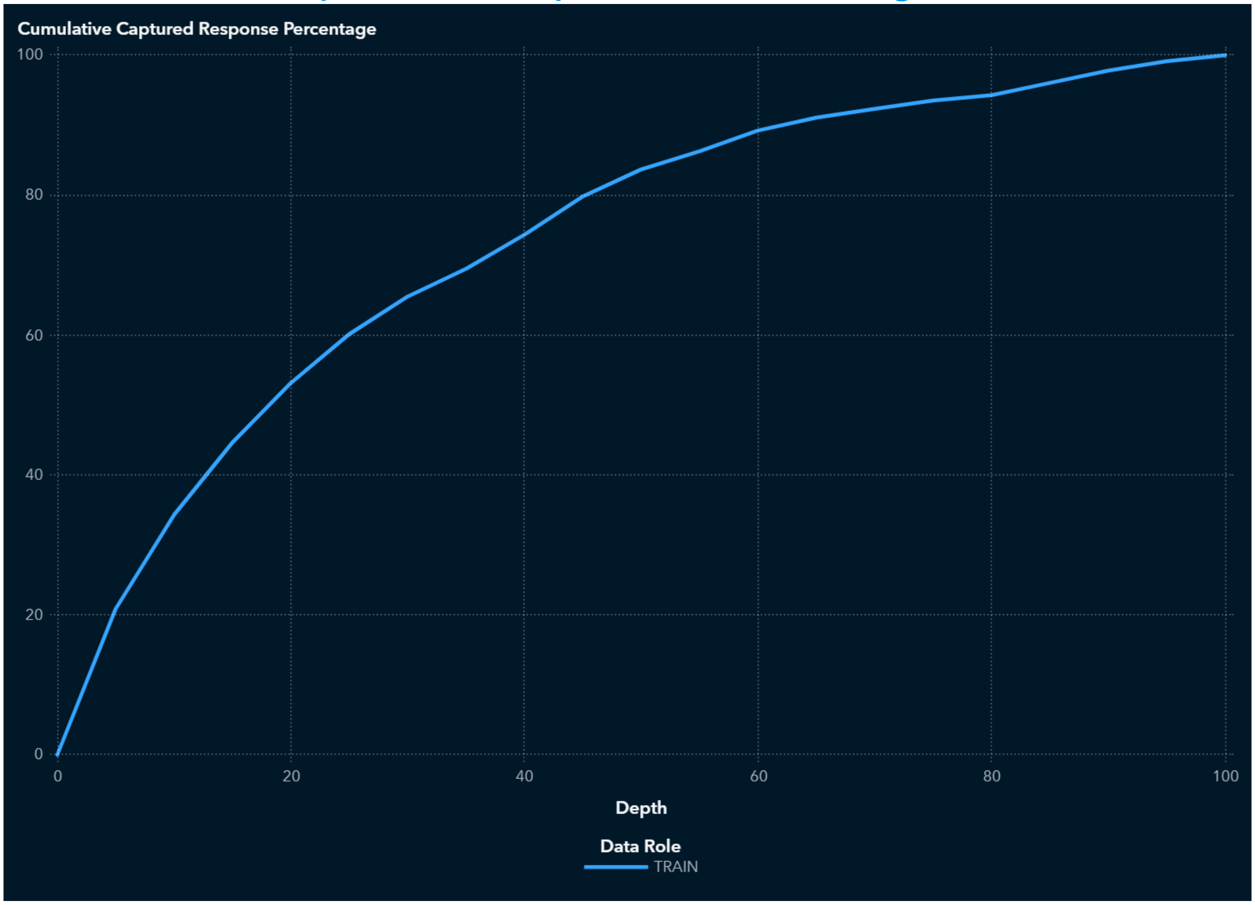
Captured Response Percentage



At the 5% quantile (depth of 5), the TRAIN partition has a Captured response percentage of 20.9 (compared to the expected value of 5 for no model). The best possible value of Captured response percentage for this partition at depth 5 is 25.06.

Captured response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. Captured response percentage is the percentage of the total number of events that are in that quantile. With no model, it is expected that 5% of the events are in each quantile.

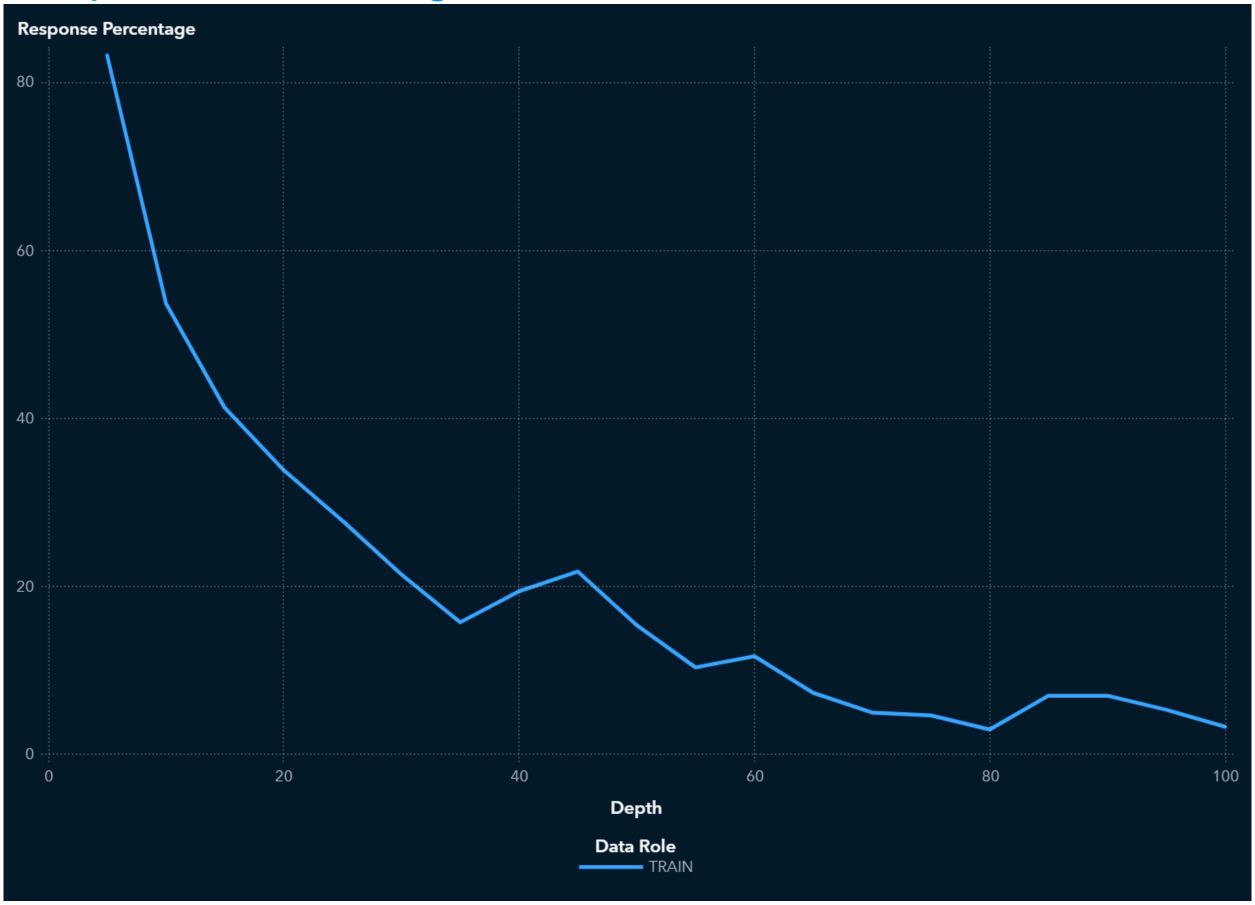
Cumulative Captured Response Percentage



In the top 10% of the data (depth 10), the TRAIN partition has a Cumulative captured response percentage of 34.3 (compared to the expected value of 10 for no model). The best possible value of Cumulative captured response percentage for this partition at depth 10 is 50.13.

Cumulative captured response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. The cumulative captured response percentage for a particular quantile is the percentage of the total number of events that are in the quantiles up to and including the current quantile. With no model, it is expected that 5% of the events are in each quantile, so the cumulative captured response percentage at depth 10 would be 10%.

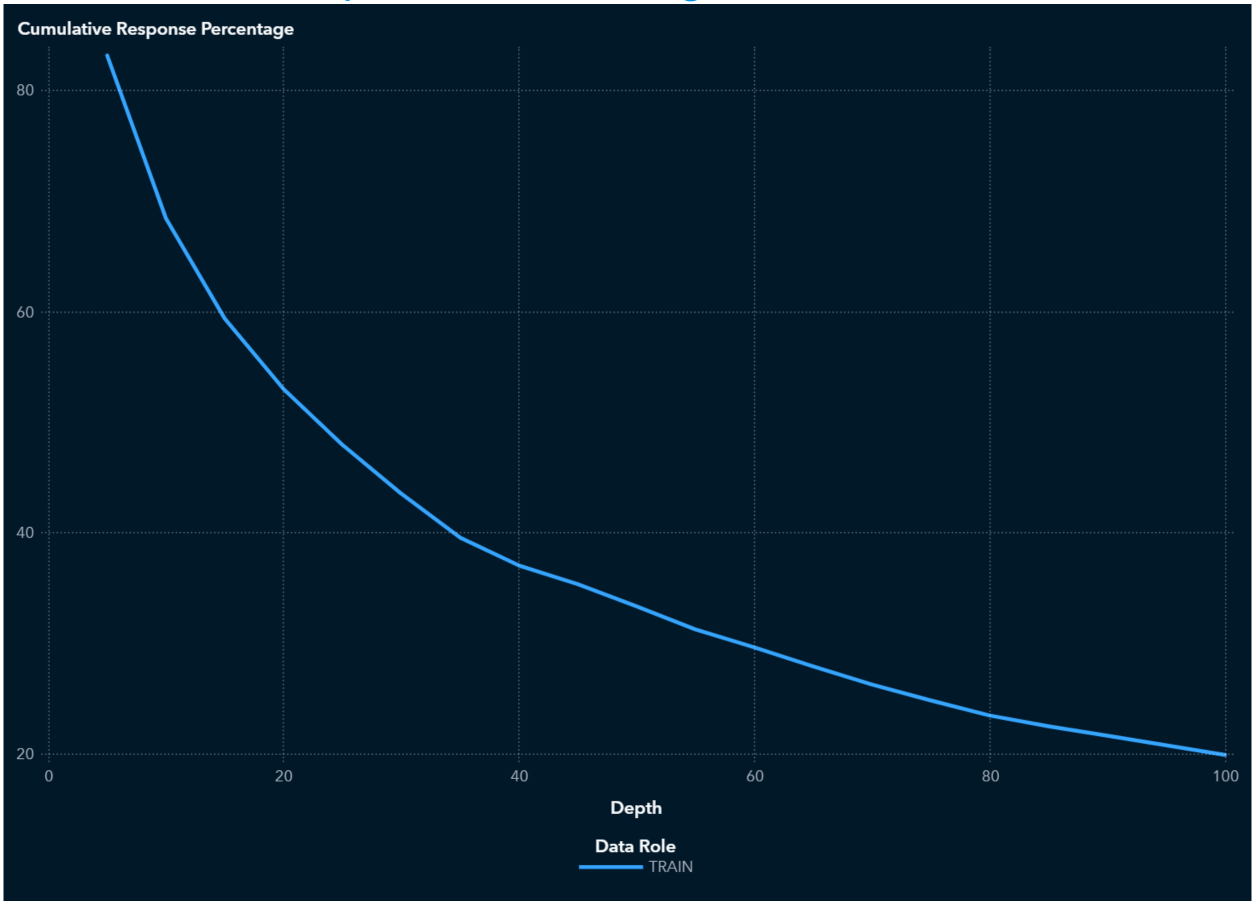
Response Percentage



At the 5% quantile (depth of 5), the TRAIN partition has a Response percentage of 83.2. The best possible value of Response percentage for this partition at depth 5 is 100.

Response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. Response percentage is the percentage of observations that are events in that quantile. With no model, it is expected that the response percentage is constant across quantiles, 100*overall-event-rate. This is also called the baseline response percentage.

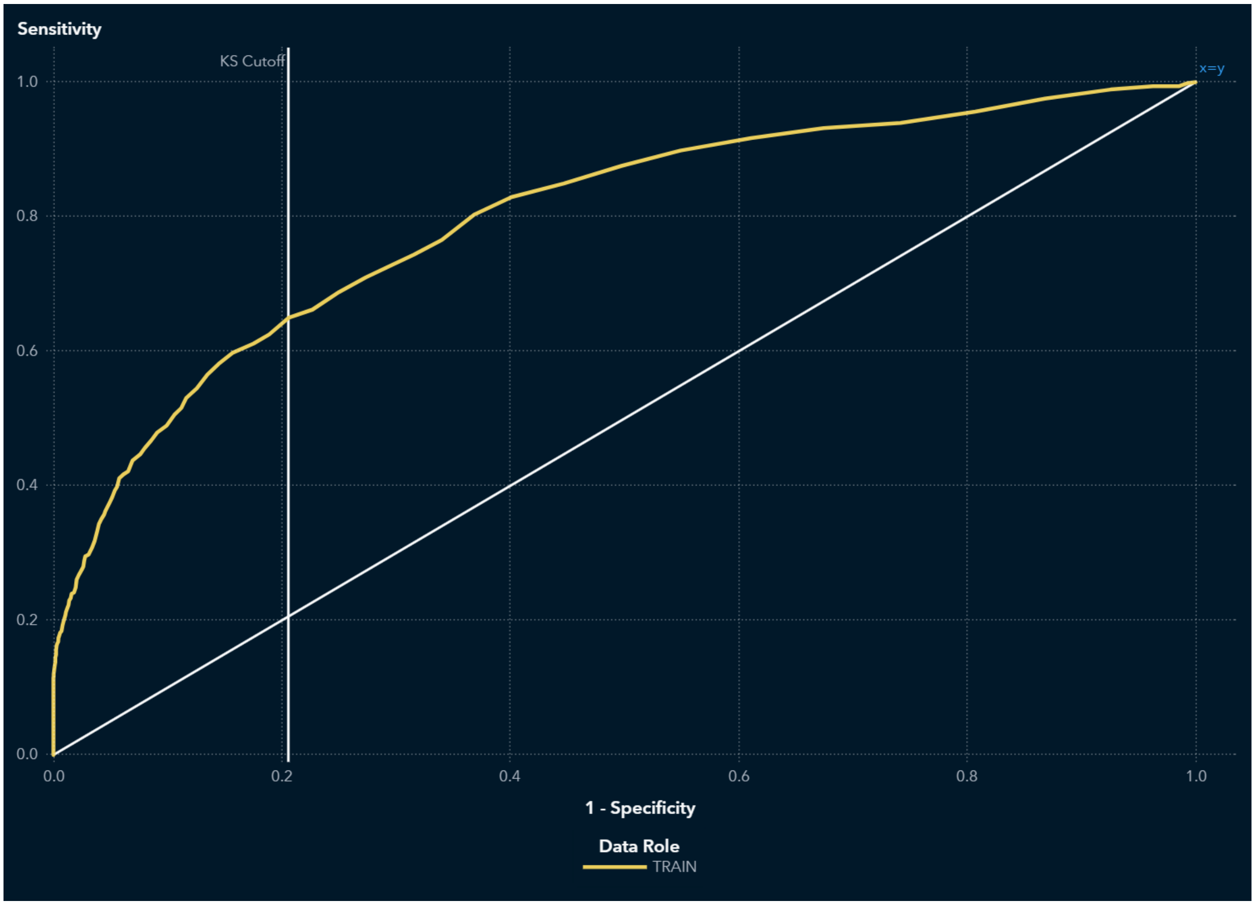
Cumulative Response Percentage



In the top 10% of the data (depth 10), the TRAIN partition has a Cumulative response percentage of 68.5. The best possible value of Cumulative response percentage for this partition at depth 10 is 100.

Cumulative response percentage is calculated by sorting in descending order each partition of the data by the predicted probability of the target event P_BAD1, which represents the predicted probability of the event "1" for the target BAD. The data is divided into 20 quantiles (demi-deciles, with 5% of the data in each), and the number of events in each quantile is computed. The cumulative response percentage for a particular quantile is the percentage of observations that are events in the quantiles up to and including the current quantile. With no model, it is expected that the response percentage is constant across quantiles, 100*overall-event-rate. This is also called the baseline response percentage.

ROC



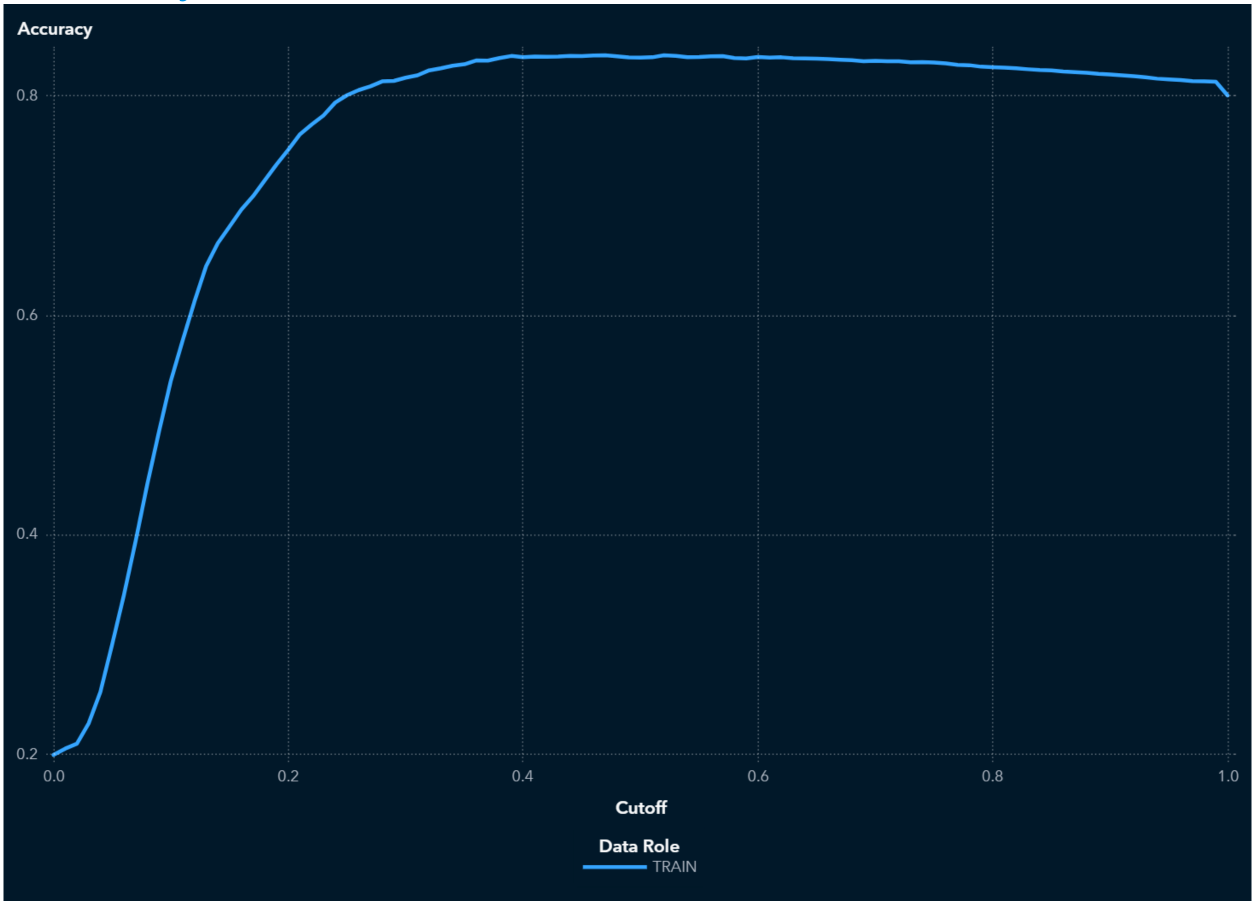
The ROC curve is a plot of sensitivity (the true positive rate) against 1-specificity (the false positive rate), which are both measures of classification based on the confusion matrix. These measures are calculated at various cutoff values. To help identify the best cutoff to use when scoring your data, the KS Cutoff reference line is drawn at the value of 1-specificity where the greatest difference between sensitivity and 1-specificity is observed for the TRAIN partition. The KS Cutoff line is drawn at the cutoff value 0.21, where the 1-specificity value is 0.206 and the sensitivity value is 0.65.

Cutoff values range from 0 to 1, inclusive, in increments of 0.01. At each cutoff value, the predicted target classification is determined by whether P_BAD1, which is the predicted probability of the event "1" for the target BAD, is greater than or equal to the cutoff value. When P_BAD1 is greater than or equal to the cutoff value, then the predicted classification is the event, otherwise it is a non-event.

The confusion matrix for each cutoff value contains four cells that display the true positives for events that are correctly classified (TP), false positives for non-events that are classified as events (FP), false negatives for events that are classified as non-events (FN), and true negatives for non-events that are classified as non-events (TN). True negatives include non-event classifications that specify a different non-event. Sensitivity is calculated as TP / (TP + FN). Specificity, the true negative rate, is calculated as TN / (TN + FP), so 1-specificity is FP / (TN + FP). The values of sensitivity and 1-specificity are plotted at each cutoff value.

A ROC curve that rapidly approaches the upper-left corner of the graph, where the difference between sensitivity and 1-specificity is the greatest, indicates a more accurate model. A diagonal line where sensitivity = 1-specificity indicates a random model.

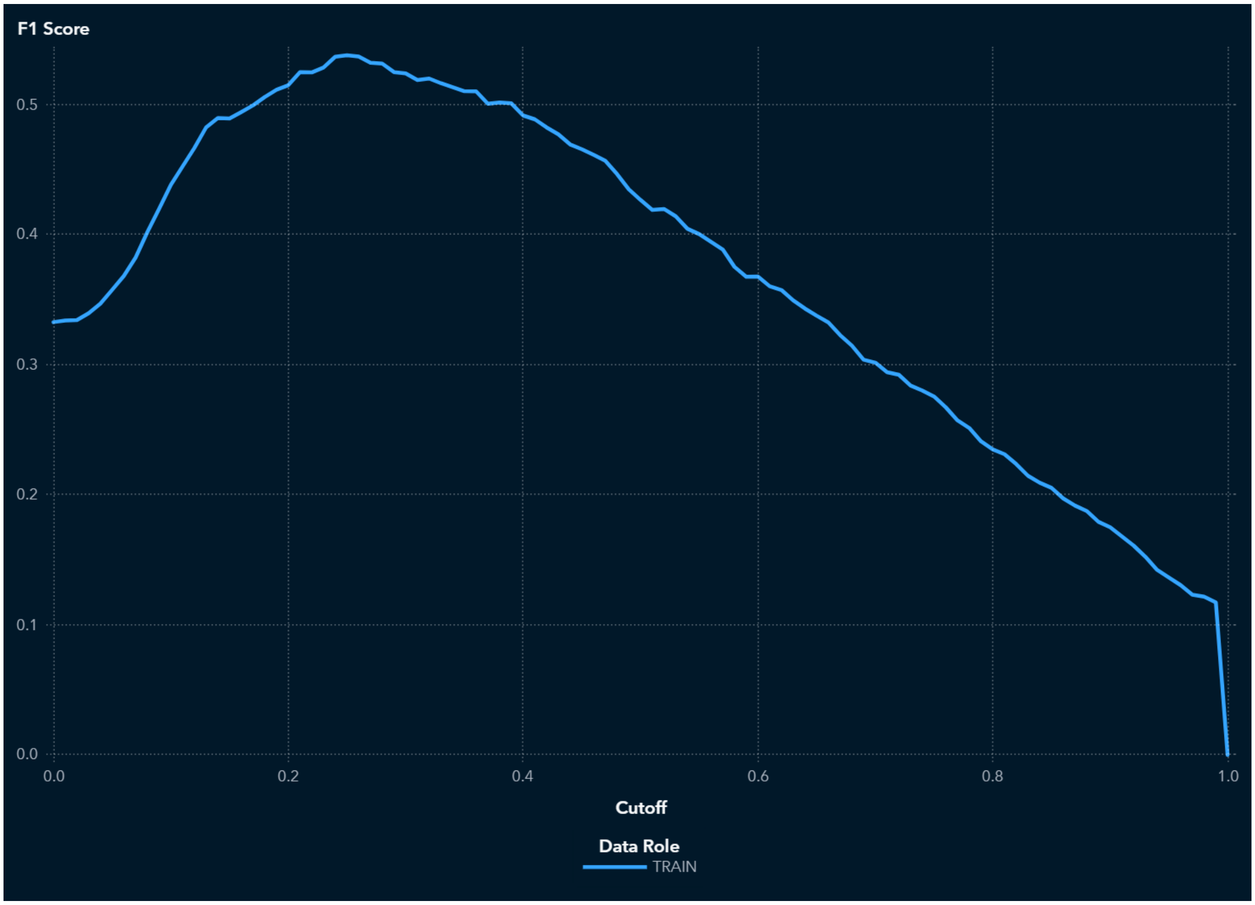
Accuracy



For this model, the accuracy in the TRAIN partition at the cutoff of 0.5 is 0.835.

Accuracy is the proportion of observations that are correctly classified as either an event or non-event, calculated at various cutoff values. Cutoff values range from 0 to 1, inclusive, in increments of 0.01. At each cutoff value, the predicted target classification is determined by whether P_BAD1, which is the predicted probability of the event "1" for the target BAD, is greater than or equal to the cutoff value. When P_BAD1 is greater than or equal to the cutoff value, then the predicted classification is the event, otherwise it is a non-event. When the predicted classification and the actual classification are both events (true positives) or both non-events (true negatives), the observation is correctly classified. If the predicted classification and actual classification disagree, then the observation is incorrectly classified. Accuracy is calculated as (true positives + true negatives) / (total observations).

F1 Score



For this model, the F1 score in the TRAIN partition at the cutoff of 0.5 is 0.427.

The F1 score combines the measures of precision and recall (or sensitivity), which are measures of classification based on the confusion matrix that are calculated at various cutoff values. Cutoff values range from 0 to 1, inclusive, in increments of 0.01. At each cutoff value, the predicted target classification is determined by whether P_BAD1, which is the predicted probability of the event "1" for the target BAD, is greater than or equal to the cutoff value. When P_BAD1 is greater than or equal to the cutoff value, then the predicted classification is the event, otherwise it is a non-event.

The confusion matrix for each cutoff value contains four cells that display the true positives for events that are correctly classified (TP), false positives for non-events that are classified as events (FP), false negatives for events that are classified as non-events (FN), and true negatives for non-events that are classified as non-events (TN). True negatives include non-event classifications that specify a different non-event.

Precision is calculated as TP / (TP + FP), and recall (or sensitivity) is calculated as TP /

(TP + FN). The F1 score is calculated as 2*Precision*Recall / (Precision + Recall), which is the harmonic mean of Precision and Recall. Larger F1 scores indicate a more accurate model.

Fit Statistics

Target Name	Data Role	Number of Observations	Average Squared Error
BAD	TRAIN	5,960	0.1204

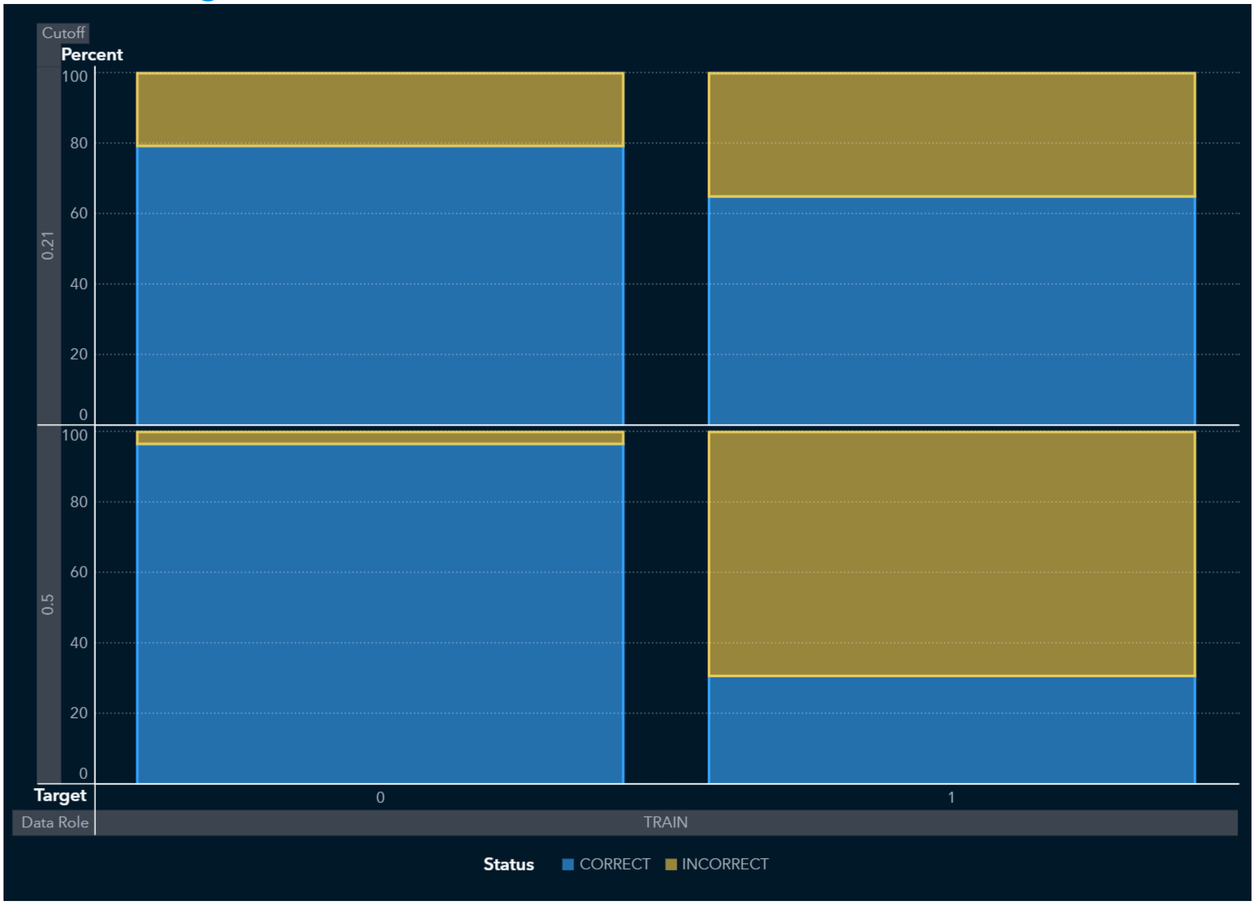
Divisor for ASE	Root Average Squared Error	Misclassification Rate	Multi-Class Log Loss
5,960	0.3470	0.1651	0.3907

KS (Youden)	Area Under ROC	Gini Coefficient	Gamma
0.4439	0.7981	0.5962	0.6062

Tau	KS Cutoff	KS at User-Specified Cutoff	Misclassification Rate at KS Cutoff (Event)
0.1904	0.2100	0.2741	0.2349

Misclassification Rate (Event)
0.1651

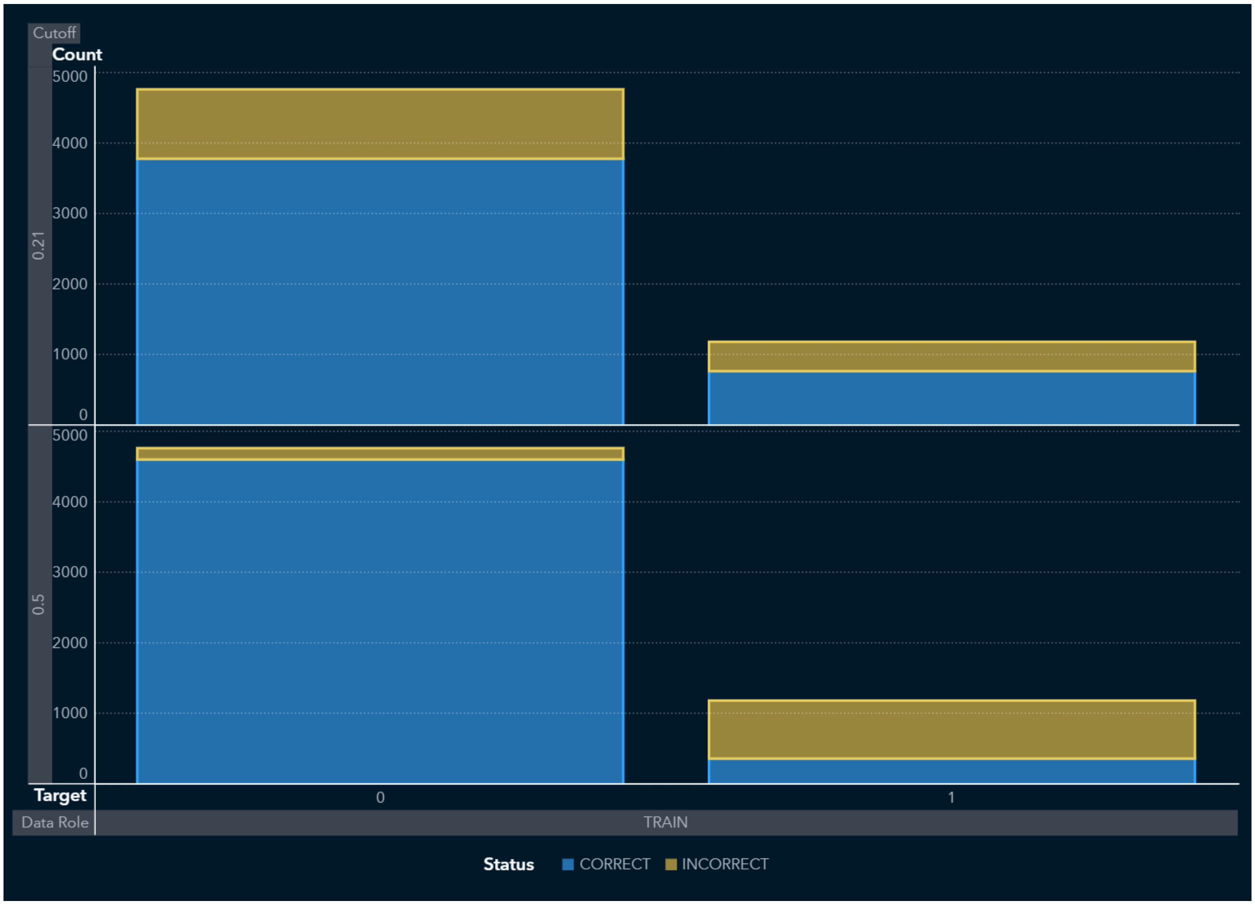
Percentage Plot



The Event Classification report is a visual representation of the confusion matrix at various cutoff values for each partition. The classification cutoffs used in the plot are the default (0.5) and the KS cutoff value 0.21 for the TRAIN partition.

For this data, for the bar corresponding to the event level of BAD, "   1", the segment of the bar colored as "CORRECT" corresponds to true positives.

Count Plot



The Event Classification report is a visual representation of the confusion matrix at various cutoff values for each partition. The classification cutoffs used in the plot are the default (0.5) and the KS cutoff value 0.21 for the TRAIN partition.

For this data, for the bar corresponding to the event level of BAD, "   1", the segment of the bar colored as "CORRECT" corresponds to true positives.

Table

Cutoff	Cutoff Source	Target Name	Response
0.2100	KS	BAD	CORRECT
0.2100	KS	BAD	INCORRECT
0.2100	KS	BAD	CORRECT
0.2100	KS	BAD	INCORRECT
0.5000	Default	BAD	CORRECT
0.5000	Default	BAD	INCORRECT
0.5000	Default	BAD	CORRECT
0.5000	Default	BAD	INCORRECT

Event	Value	Training Frequency	Validation Frequency
1	True Positive	773	
1	False Negative	416	
0	True Negative	3,787	
0	False Positive	984	
1	True Positive	366	
1	False Negative	823	
0	True Negative	4,610	
0	False Positive	161	

Test Frequency	Training Percentage	Validation Percentage	Test Percentage
	65.0126		
	34.9874		
	79.3754		
	20.6246		
	30.7822		
	69.2178		
	96.6254		

Test Frequency	Training Percentage	Validation Percentage	Test Percentage
	3.3746		

Properties

Property Name	Property Value
binaryProbCutoff	0.5000
chooseCriterion	SBC
classCoding	GLM
classOrder	FMTASC
codeLocation	mlearning
dataMiningVersion	V2024.03
exactPctlLift	true
explainFidelity	false
explainInfo	false
factorInteractions	false
factorSplit	false
fullDatasetReconstitution	false
hierarchy	NONE
icePlots	false
informativeMiss	false
linkFunction	LOGIT
maxEffects	0
maxNumShapVars	20
maxSteps	0
minEffects	0
missAsLvl	false
nBins	50
nomlinkFunction	GLOGIT
normalize	true
pdNumImportantInputs	5
pdObsSamples	1,000

Property Name	Property Value
pdPlots	false
performKernelShap	false
performLime	false
performVI	false
polynomialDegree	2
reportingOnly	false
seedId	12,345
selectCriterion	SBC
selectMethod	FORWARD
slEntry	0.0500
slStay	0.0500
specifyRows	RANDOM
stopCriterion	SBC
suppressIntercept	false
tech	NRRIDG
templateRevision	2
train	true
truncateLl	5
truncateUl	95
usePolynomial	false
useSpline	false
useSplineSplit	false
userProbCutoff	false

Output

The SAS System

The GENSELECT Procedure

Model Information	
Data Source	_INPUT_6T6ARBC7G3R2BQXFXPN8OZ0ZQ
Response Variable	BAD
Distribution	Binary
Link Function	Logit
Optimization Technique	Newton-Raphson with Ridging
Predicted Response Level	I_BAD

Number of Observations Read	5960
Number of Observations Used	5960

Response Profile		
Ordered Value	BAD	Total Frequency
1	0	4771
2	1	1189

Probability modeled is BAD = 1.

Class Level Information		
Class	Levels	Values
IMP_DELINQ	14	0 1 2 3 4 5 6 7 8 10 11 12 13 15
IMP_DEROG	11	0 1 2 3 4 5 6 7 8 9 10
IMP_JOB	6	Mgr Office Other ProfExe Sales Self
IMP_NINQ	16	0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 17
IMP_REASON	2	DebtCon HomeImp

Selection Information	
Selection Method	Forward
Select Criterion	SBC
Choose Criterion	SBC
Stop Criterion	SBC
Effect Hierarchy Enforced	None
Stop Horizon	3

Selection Details

Convergence criterion (GCONV=1E-8) satisfied. Quasi-complete separation possibly detected.

Selection Summary			
Step	Effect Entered	Number Effects In	SBC
0	Intercept	1	5965.1625
1	IMP_DELINQ	2	5314.3655
2	IMP_DEROG	3	5235.5867
3	IM_CLAGE	4	5099.4411
4	IM_DEBTINC	5	4996.3894
5	LOAN	6	4980.1606
6	IMP_JOB	7	4962.6008
7	IM_CLNO	8	4950.7771
8	IMP_REASON	9	4952.8749
9	IMP_VALUE	10	4956.3960
10	IM_MORTDUE	11	4949.1240
11	IM_YOJ	12	4943.8914*
12	IMP_NINQ	13	4955.5952
* Optimal Value Of Criterion			

Selection stopped because all effects are in the model.

The model at step 11 is selected where SBC is 4943.891.

Selected Effects:	Intercept IMP_VALUE IM_CLAGE IM_CLNO IM_DEBTINC IM_MORTDUE IM_YOJ LOAN IMP_DELINQ IMP_DEROG IMP_JOB IMP_REASON

Selected Model

Dimensions	
Columns in Design	41
Number of Effects	12
Max Effect Columns	14
Rank of Design	37
Parameters in Optimization	37

Fit Statistics	
-2 Log Likelihood	4656.95638
AIC (smaller is better)	4722.95638
AICC (smaller is better)	4723.33505
SBC (smaller is better)	4943.81963

Parameter Estimates					
Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	23.942790	455.952363	0.0028	0.9581
IMP_VALUE	0	0.000003730	.	.	.
IM_CLAGE	0	-0.006078	.	.	.
IM_CLNO	1	-0.012250	0.004329	8.0086	0.0047
IM_DEBTINC	1	0.052817	0.006078	75.5087	<.0001
IM_MORTDUE	0	-0.000004318	.	.	.
IM_YOJ	1	-0.013145	0.005781	5.1703	0.0230
LOAN	0	-0.000018078	.	.	.
IMP_DELINQ 0	1	-12.191553	384.214677	0.0010	0.9747
IMP_DELINQ 1	1	-10.971674	384.214678	0.0008	0.9772
IMP_DELINQ 2	1	-10.744061	384.214691	0.0008	0.9777
IMP_DELINQ 3	1	-10.166933	384.214708	0.0007	0.9789
IMP_DELINQ 4	1	-9.688172	384.214752	0.0006	0.9799
IMP_DELINQ 5	1	-8.113967	384.214958	0.0004	0.9832
IMP_DELINQ 6	1	1.441909	389.184649	0.0000	0.9970
IMP_DELINQ 7	1	1.471267	397.112440	0.0000	0.9970
IMP_DELINQ 8	1	1.439234	420.391770	0.0000	0.9973
IMP_DELINQ 10	1	1.892153	469.053838	0.0000	0.9968
IMP_DELINQ 11	1	2.551858	462.069997	0.0000	0.9956
IMP_DELINQ 12	1	3.087631	543.361463	0.0000	0.9955
IMP_DELINQ 13	1	3.588408	543.361579	0.0000	0.9947
IMP_DELINQ 15	0	0	.	.	.
IMP_DEROG 0	1	-13.250900	245.502866	0.0029	0.9570
IMP_DEROG 1	1	-12.341425	245.502888	0.0025	0.9599
IMP_DEROG 2	1	-12.011793	245.502929	0.0024	0.9610
IMP_DEROG 3	1	-10.977605	245.503094	0.0020	0.9643
IMP_DEROG 4	1	-10.696803	245.503455	0.0019	0.9652
IMP_DEROG 5	1	-11.725995	245.503564	0.0023	0.9619
IMP_DEROG 6	1	-10.934791	245.503610	0.0020	0.9645
IMP_DEROG 7	1	-0.591805	265.193829	0.0000	0.9982
IMP_DEROG 8	1	-0.199370	280.287940	0.0000	0.9994
IMP_DEROG 9	1	-0.945488	315.724867	0.0000	0.9976
IMP_DEROG 10	0	0	.	.	.
IMP_JOB Mgr	1	-0.522121	0.215751	5.8565	0.0155
IMP_JOB Office	1	-1.199265	0.220966	29.4563	<.0001
IMP_JOB Other	1	-0.503031	0.200332	6.3051	0.0120
IMP_JOB ProfExe	1	-0.607401	0.207839	8.5408	0.0035
IMP_JOB Sales	1	0.267274	0.308085	0.7526	0.3856
IMP_JOB Self	0	0	.	.	.
IMP_REASON DebtCon	1	-0.191334	0.083876	5.2037	0.0225
IMP_REASON HomeImp	0	0	.	.	.

Score Code Variables for Predicted Probability	
BAD	Variable
1	P_BAD1
0	P_BAD0

Task Timing		
Task	Seconds	Percent
Setup and Parsing	0.01	1.87%
Levelization	0.00	0.79%
Model Initialization	0.00	0.44%
SSCP Computation	0.01	1.72%
Model Selection	0.34	94.65%
Producing Score Code	0.00	0.34%
Display	0.00	0.10%
Cleanup	0.00	0.00%
Total	0.36	100.00%