Accident_Fatality_Predict...

"Logistic Regression" Results

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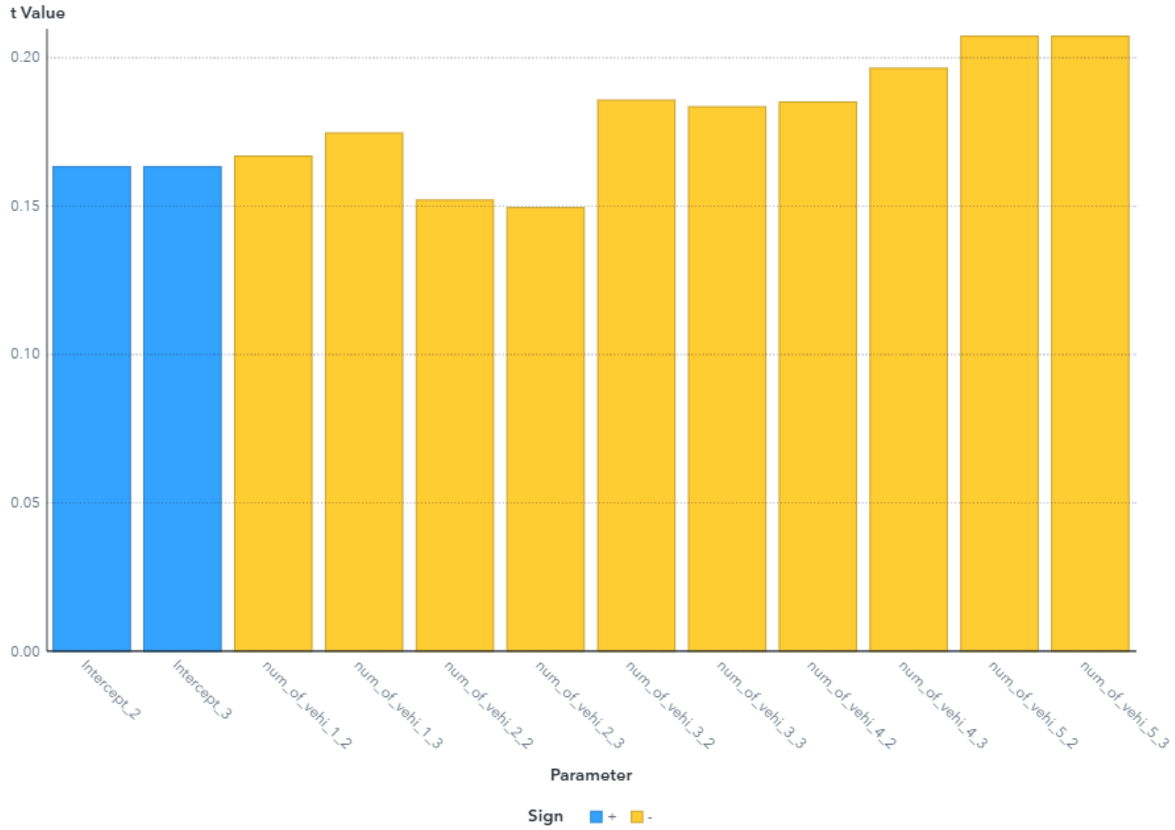
Contents

t Values by Parameter	3
Parameter Estimates	4
Selection Summary	6
Regression Fit Statistics	7
Score Inputs	8
Score Outputs	9
Cumulative Lift	11
Lift	13
Gain	14
Captured Response Percentage	15
Cumulative Captured Response Percentage	16
Response Percentage	17
Cumulative Response Percentage	18
ROC	19
Accuracy	21
F1 Score	22
Fit Statistics	24
Percentage Plot	25
Count Plot	26
Table	27
Percentage Plot	28
Count Plot	29
Table	30
Properties	32
Output	34

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 target level 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 the target level as the parameter value increases. The target level to which the parameter estimate corresponds is suffixed to the parameter name (for a cumulative link model, this is only true for the intercept). The most significant parameter is num_of_vehi for the target level "2" with a t value of -0.207.

Parameter Estimates

Effect	Parameter	t Value	Sign
Intercept	Intercept_3	0.1633	+
Intercept	Intercept_2	0.1633	+
num_of_vehi	num_of_vehi_1_3	0.1747	-
num_of_vehi	num_of_vehi_1_2	0.1669	-
num_of_vehi	num_of_vehi_2_3	0.1496	-
num_of_vehi	num_of_vehi_2_2	0.1521	-
num_of_vehi	num_of_vehi_3_3	0.1836	-
num_of_vehi	num_of_vehi_3_2	0.1858	-
num_of_vehi	num_of_vehi_4_3	0.1965	-
num_of_vehi	num_of_vehi_4_2	0.1851	-
num_of_vehi	num_of_vehi_5_3	0.2073	-
num_of_vehi	num_of_vehi_5_2	0.2073	-
num_of_vehi	num_of_vehi_7_3		+
num_of_vehi	num_of_vehi_7_2		+

Estimate	Absolute Estimate	Standard Error	Chi-Square
8.6263	8.6263	52.8104	0.0267
8.6263	8.6263	52.8104	0.0267
-9.2258	9.2258	52.8105	0.0305
-8.8148	8.8148	52.8105	0.0279
-7.8997	7.8997	52.8105	0.0224
-8.0341	8.0341	52.8105	0.0231
-9.6936	9.6936	52.8106	0.0337
-9.8113	9.8113	52.8107	0.0345
-10.3780	10.3780	52.8111	0.0386
-9.7773	9.7773	52.8108	0.0343
-10.9487	10.9487	52.8125	0.0430
-10.9487	10.9487	52.8125	0.0430
0	0		
0	0		

Pr > Chi-Square	Degrees of Freedom	Predicted Outcome
0.8702	1	3
0.8702	1	2
0.8613	1	3
0.8674	1	2
0.8811	1	3
0.8791	1	2
0.8544	1	3
0.8526	1	2
0.8442	1	3
0.8531	1	2
0.8358	1	3
0.8358	1	2
	0	3
	0	2

Selection Summary

Step	Effect Entered	Effect Removed	Number of Effects
0	Intercept		1
1	num_of_vehi		2
2	loc_auth_ons_distr		3
3		loc_auth_ons_distr	2

SBC	Optimal SBC
5,422.2064	0
5,143.4869	0
4,957.5827	0
4,866.5311	1

Regression Fit Statistics

Statistic	Description	Training	Testing
M2LL	-2 Log Likelihood	5,044.0705	2,158.7138
AIC	AIC (smaller is better)	5,068.0705	2,182.7138
AICC	AICC (smaller is better)	5,068.1978	2,183.0132
SBC	SBC (smaller is better)	5,137.7850	2,242.2494
ASE	Average Square Error	0.6162	0.6168

Score Inputs

Name	Role	Variable Level	Type
num_of_vehi	INPUT	NOMINAL	N

Variable Type	Variable Label	Variable Format	Variable Length
double			8

Score Outputs

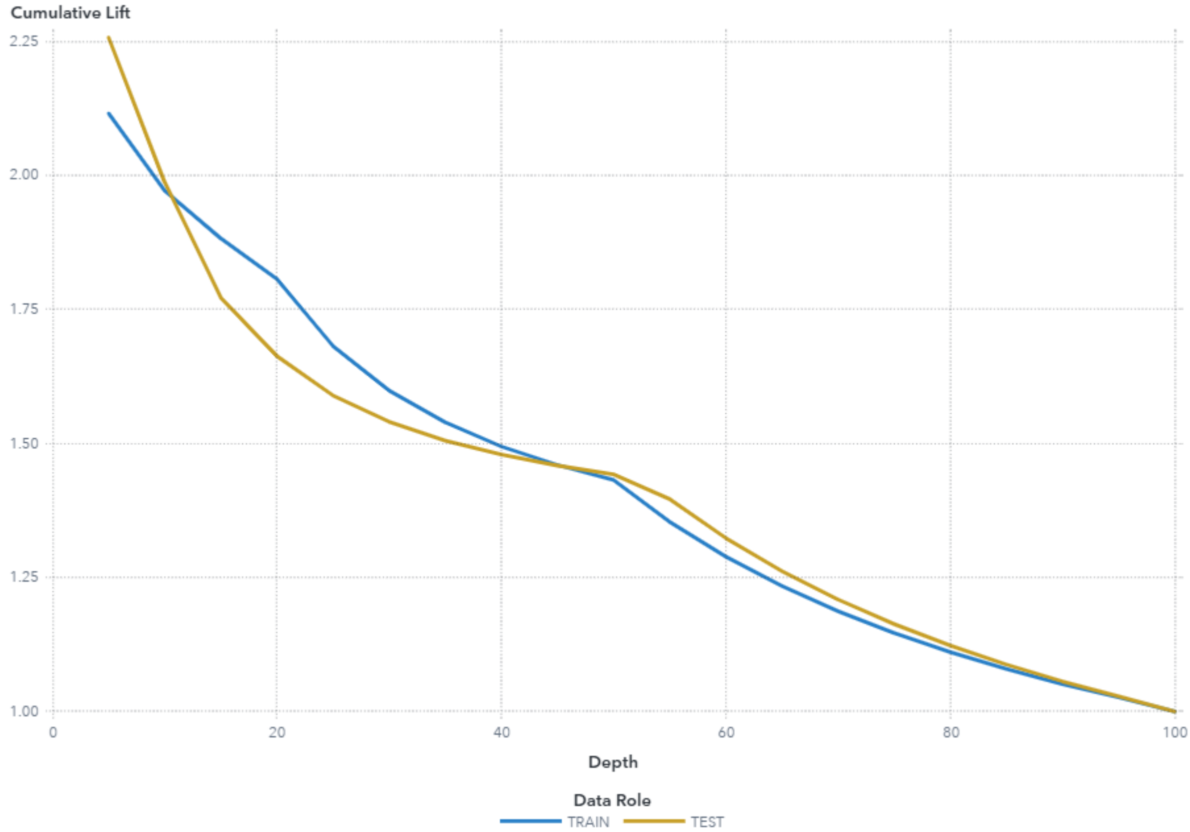
Name	Role	Type	Variable Type
EM_CLASSIFICATION	CLASSIFICATION	C	char
EM_EVENTPROBABILITY	PREDICT	N	double
EM_PROBABILITY	PREDICT	N	double
I_acci_severity	CLASSIFICATION	C	char
P_acci_severity1	PREDICT	N	double
P_acci_severity2	PREDICT	N	double
P_acci_severity3	PREDICT	N	double

Variable Label	Variable Format	Variable Length	Creator
Predicted for acci_severity		12	logisticreg
Probability for acci_severity=1		8	logisticreg
Probability of Classification		8	logisticreg
Into: acci_severity		12	logisticreg
Predicted: acci_severity=1		8	logisticreg
Predicted: acci_severity=2		8	logisticreg
Predicted: acci_severity=3		8	logisticreg

Function	Creator GUID
CLASSIFICATION	637f35cd-d552-4e3f-9abb-4c689142a3aa
PREDICT	637f35cd-d552-4e3f-9abb-4c689142a3aa
PREDICT	637f35cd-d552-4e3f-9abb-4

Function	Creator GUID
	c689142a3aa
CLASSIFICATION	637f35cd-d552-4e3f-9abb-4c689142a3aa
PREDICT	637f35cd-d552-4e3f-9abb-4c689142a3aa
PREDICT	637f35cd-d552-4e3f-9abb-4c689142a3aa
PREDICT	637f35cd-d552-4e3f-9abb-4c689142a3aa

Cumulative Lift

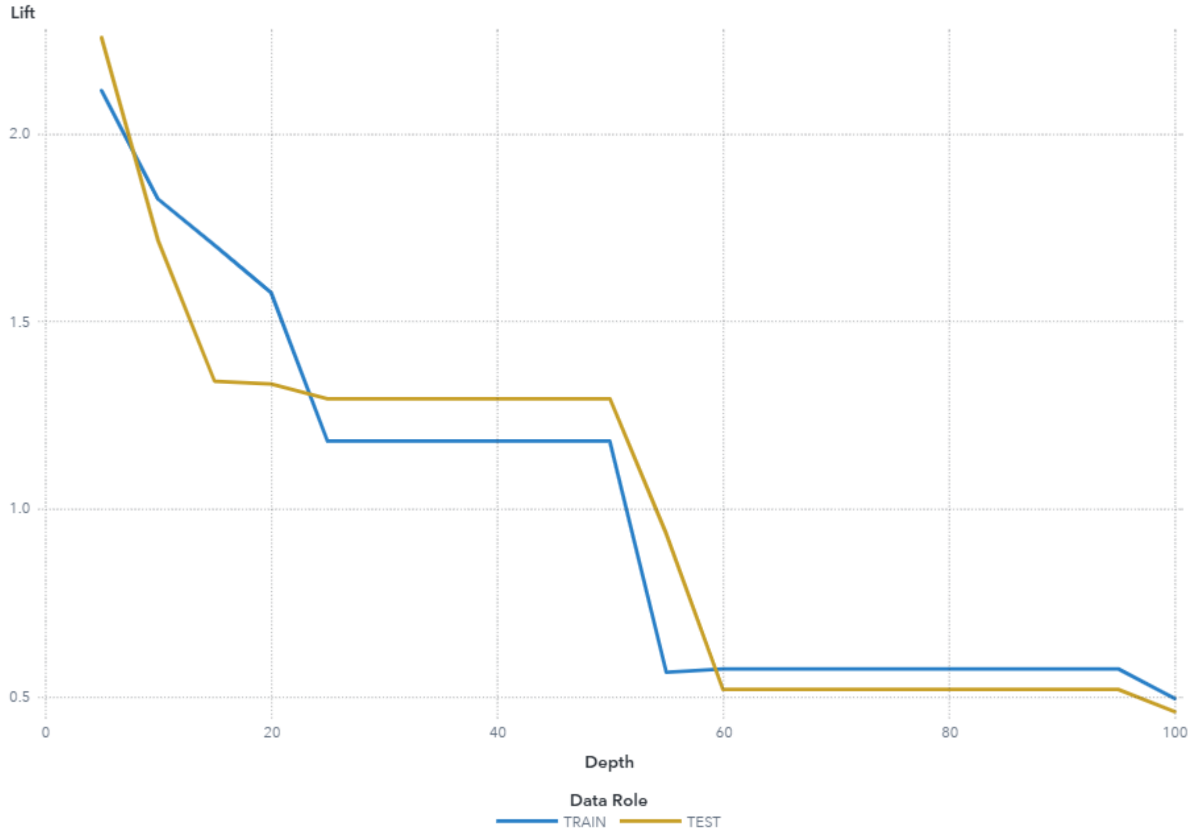


The TRAIN partition has a Cumulative Lift of 1.97 in the 10% quantile (depth of 10) meaning there are 1.97 times more events in the first two quantiles than expected by random (10% of the total number of events). Because this value is greater than 1, it is better to use your model to identify responders than no model, based on the selected partition.

The TEST partition has a Cumulative Lift of 1.99 in the 10% quantile (depth of 10) meaning there are 1.99 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_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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

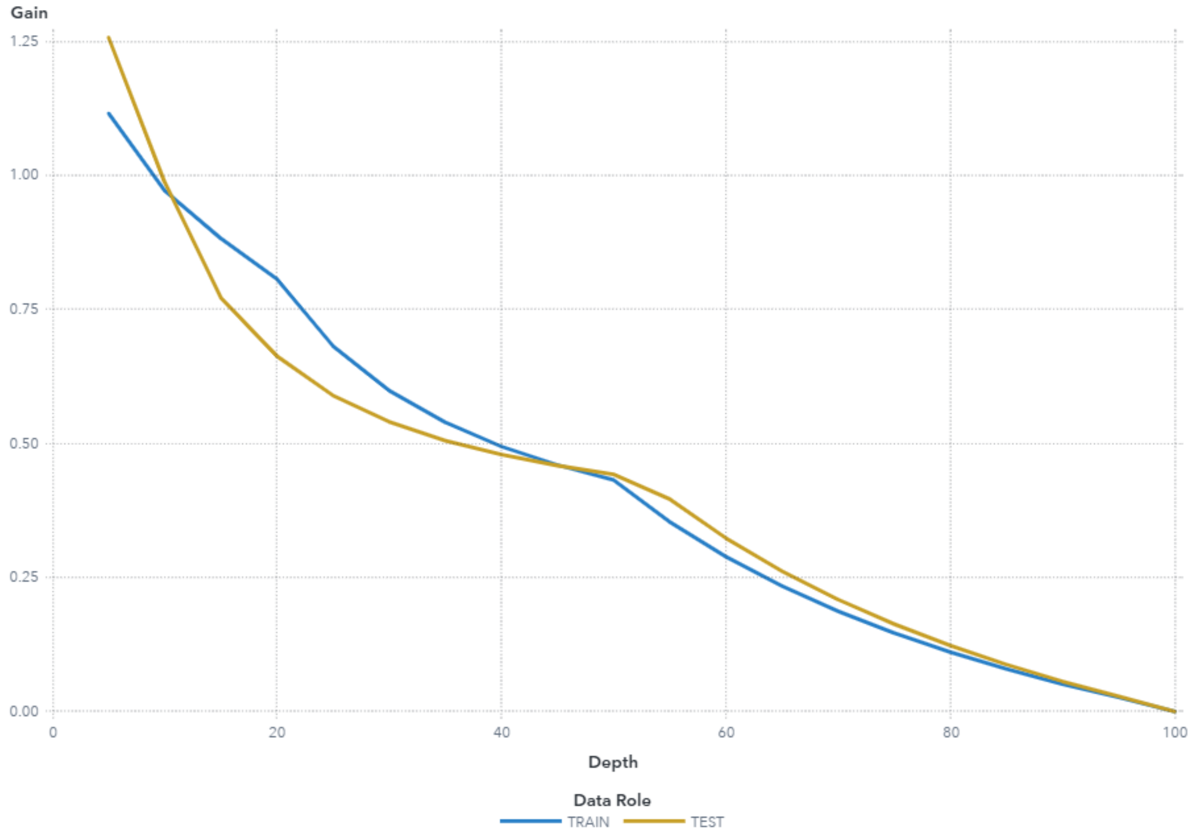


The TRAIN partition has a Lift of 2.12 in the 5% quantile (depth of 5) meaning there are 2.12 times more events in that quantile than expected by random (5% of the total number of events). Because this value is greater than 1, it is better to use your model to identify responders than no model, based on the selected partition.

The TEST partition has a Lift of 2.26 in the 5% quantile (depth of 5) meaning there are 2.26 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_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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

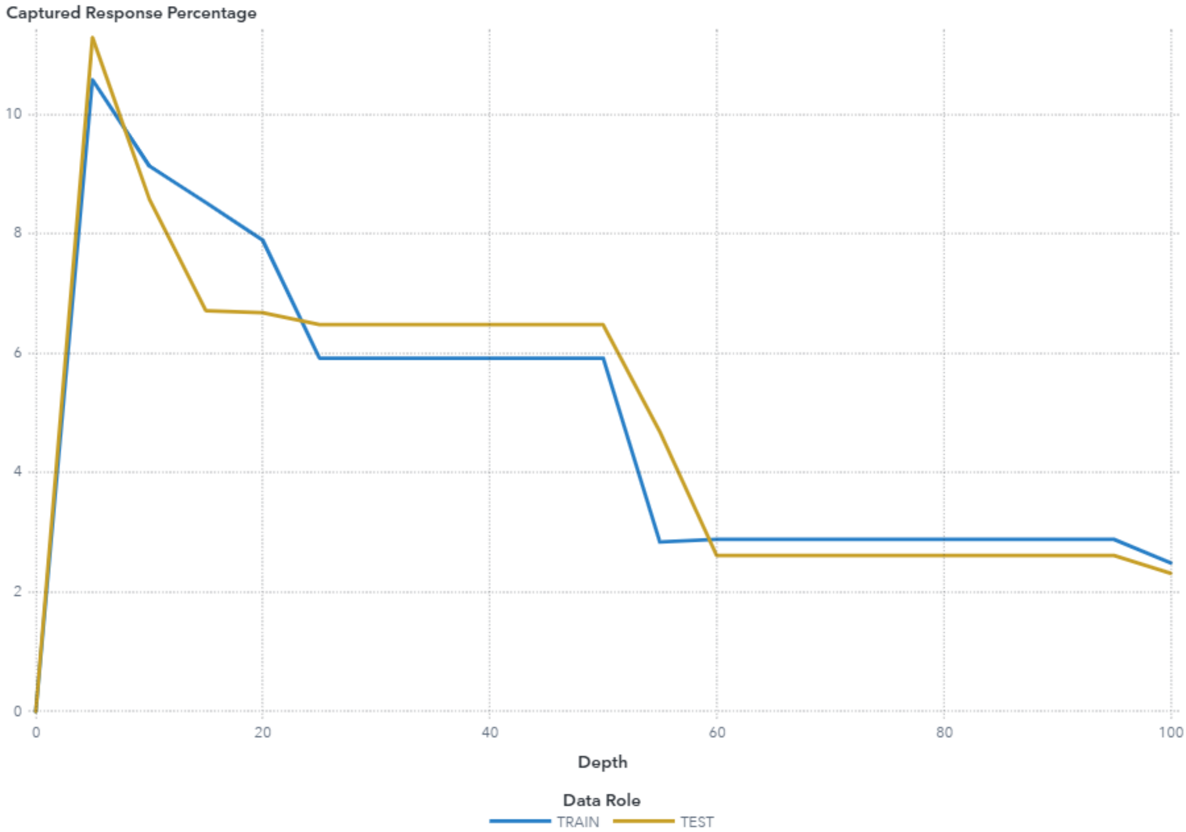


The TRAIN partition has a Gain of 1 at the 10% quantile (depth of 10). Because this value is greater than 0, it is better to use your model to identify responders than no model, based on the selected partition. The best possible value of Gain for this partition at depth 10 is 1.81.

The TEST partition has a Gain of 1 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 1.8.

Gain is calculated by sorting each partition in descending order by the predicted probability of the target event P_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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

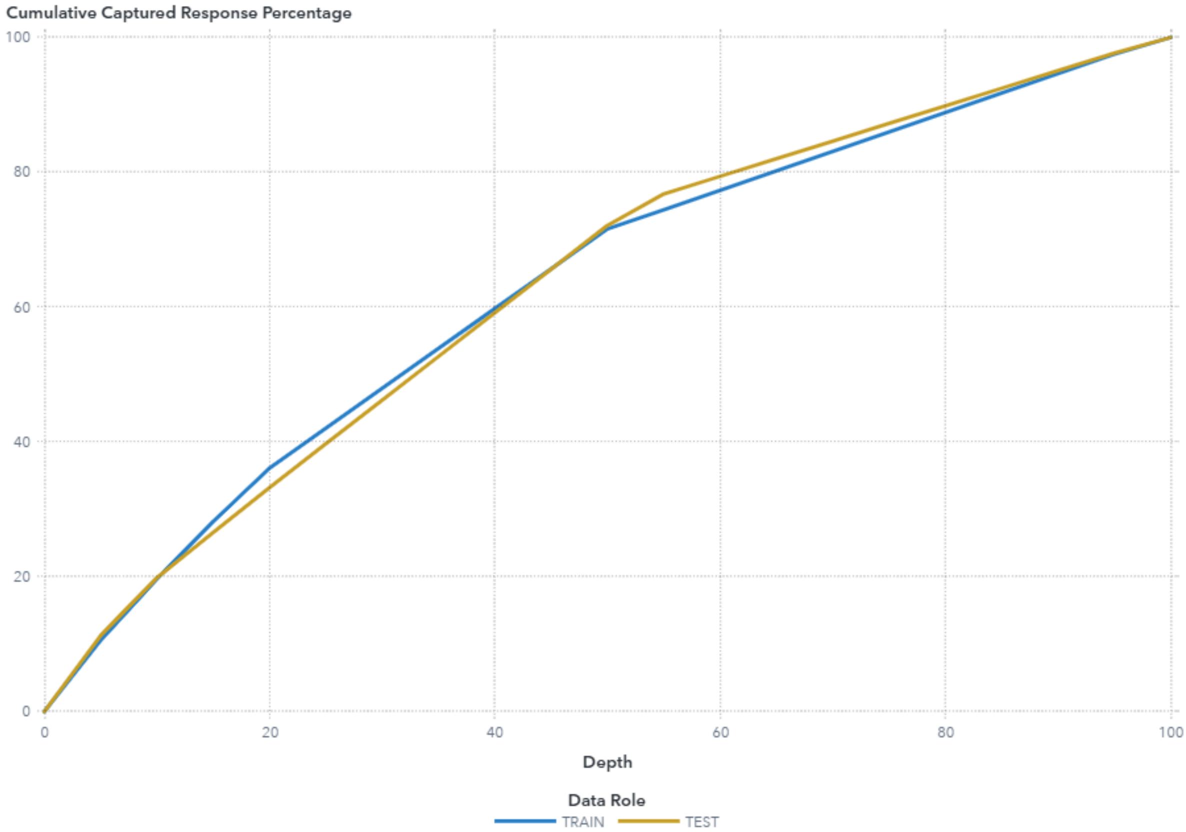


At the 5% quantile (depth of 5), the TRAIN partition has a Captured response percentage of 10.6 (compared to the expected value of 5 for no model). The best possible value of Captured response percentage for this partition at depth 5 is 14.06.

At the 5% quantile (depth of 5), the TEST partition has a Captured response percentage of 11.3 (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 14.02.

Captured response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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

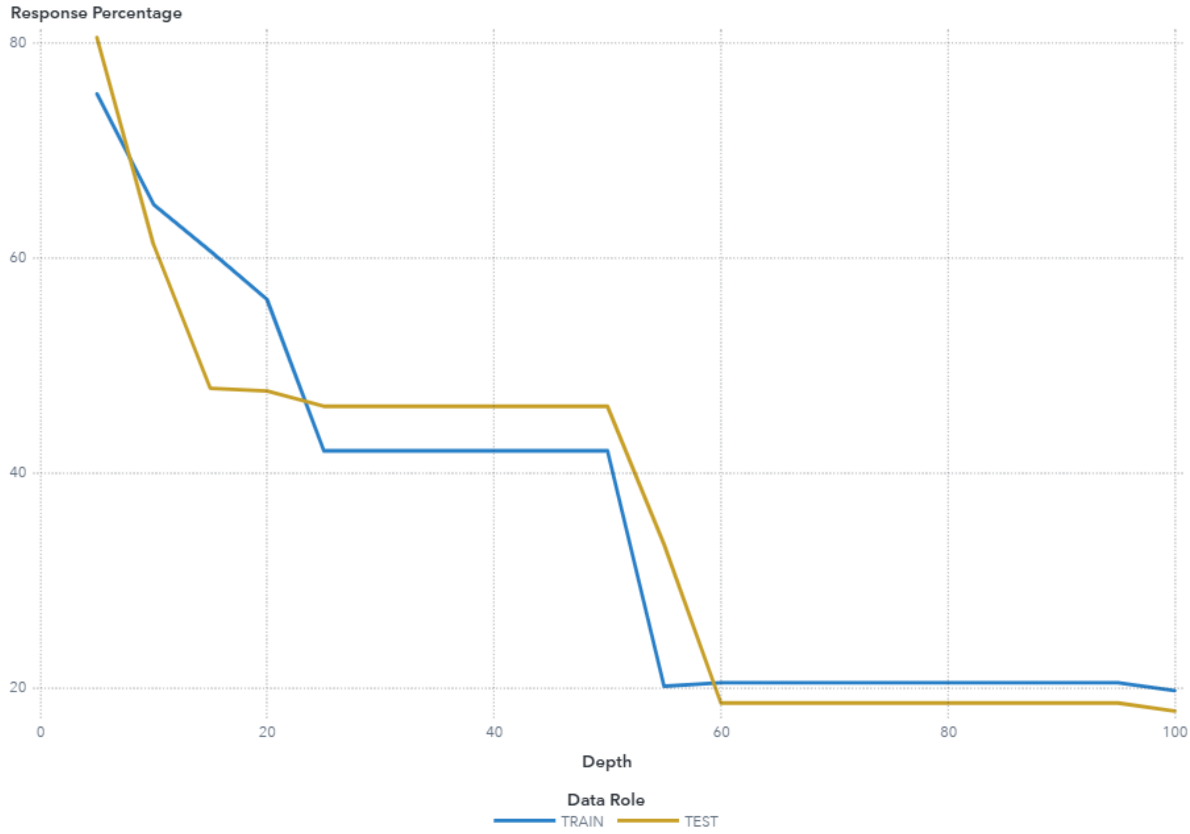


In the top 10% of the data (depth 10), the TRAIN partition has a Cumulative captured response percentage of 19.7 (compared to the expected value of 10 for no model). The best possible value of Cumulative captured response percentage for this partition at depth 10 is 28.12.

In the top 10% of the data (depth 10), the TEST partition has a Cumulative captured response percentage of 19.9 (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 28.04.

Cumulative captured response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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

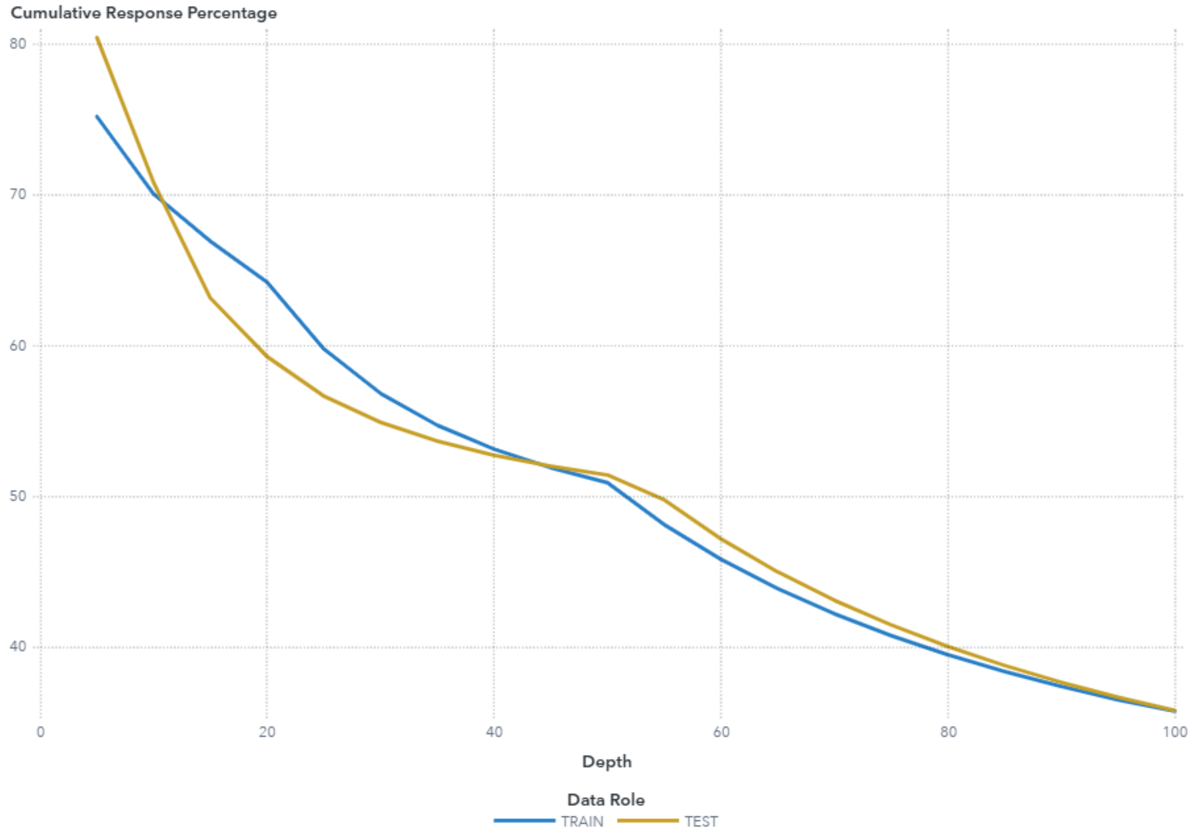


At the 5% quantile (depth of 5), the TRAIN partition has a Response percentage of 75.2. The best possible value of Response percentage for this partition at depth 5 is 100.

At the 5% quantile (depth of 5), the TEST partition has a Response percentage of 80.5. 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_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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

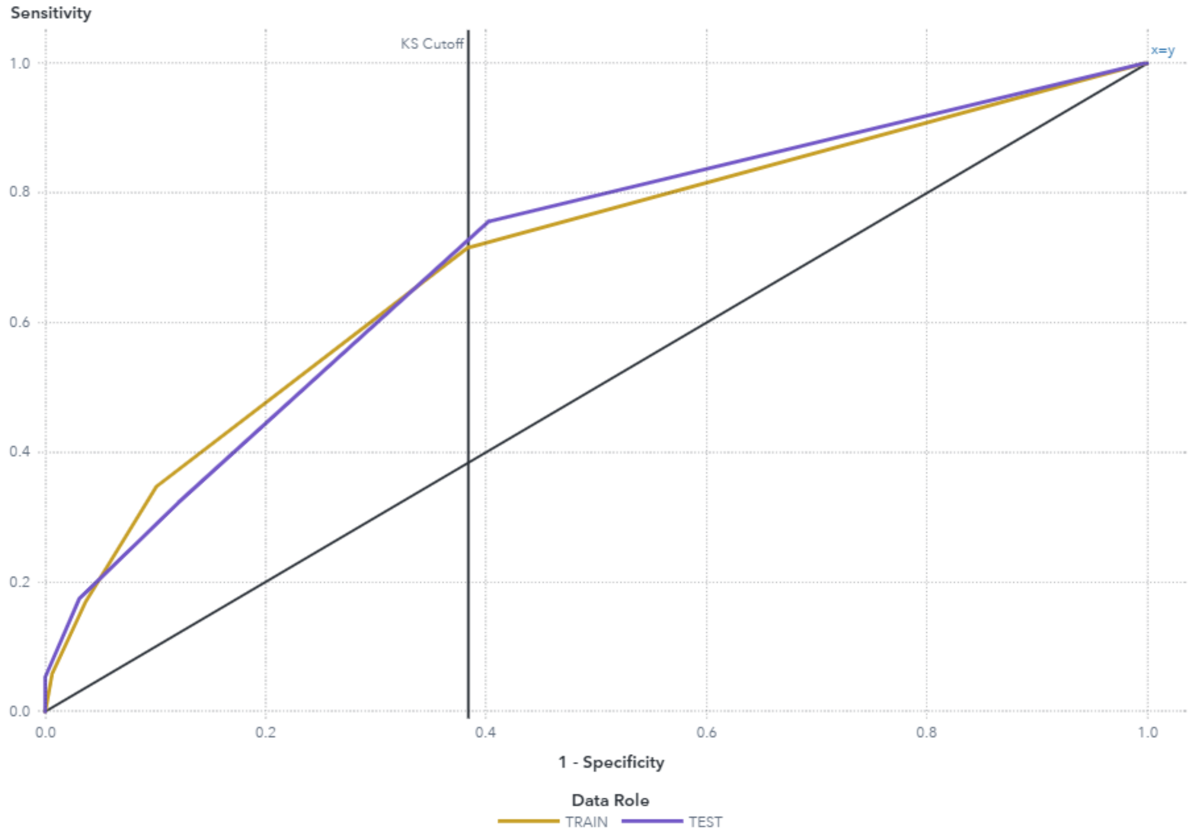


In the top 10% of the data (depth 10), the TRAIN partition has a Cumulative response percentage of 70.1. The best possible value of Cumulative response percentage for this partition at depth 10 is 100.

In the top 10% of the data (depth 10), the TEST partition has a Cumulative response percentage of 70.8. 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_acci_severity1, which represents the predicted probability of the event "1" for the target acci_severity. 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



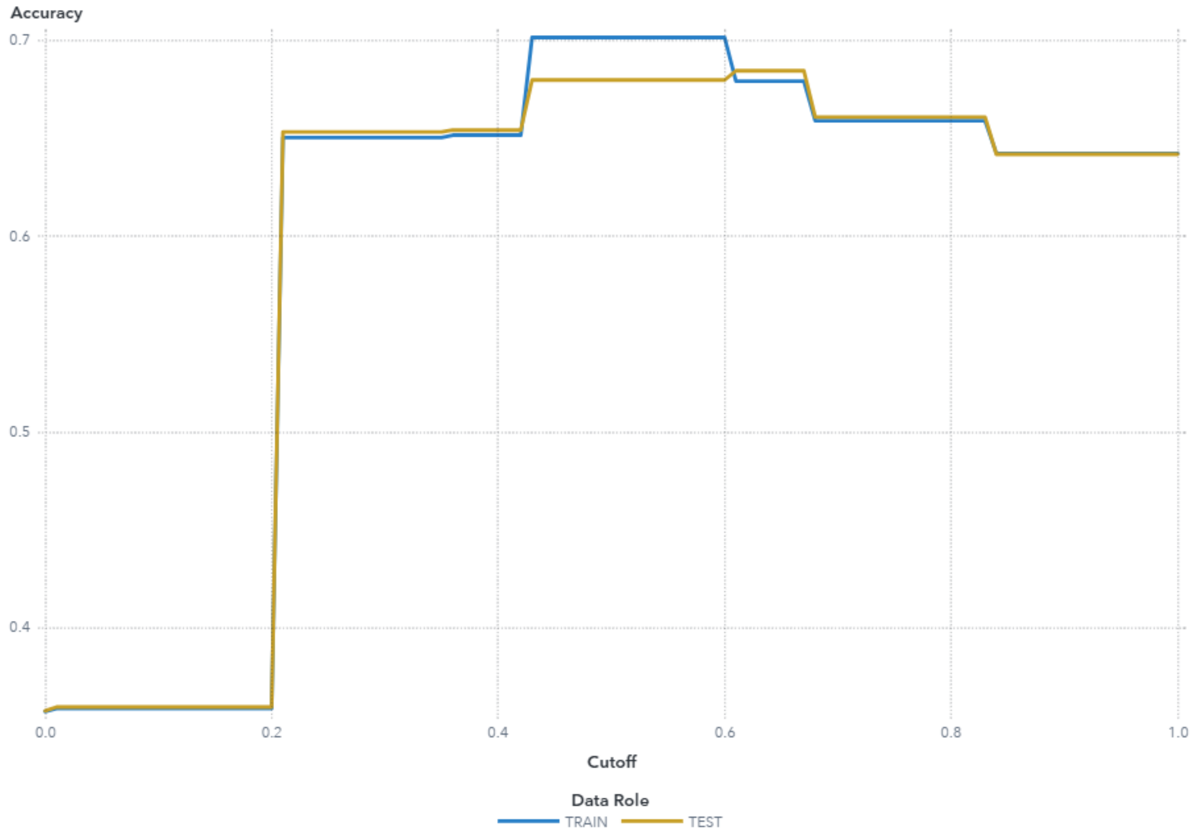
The ROC curve is a plot of sensitivity (the true positive rate) against 1-specificity (the false positive rate), which are both measures of classification based on the confusion matrix. These measures are calculated at various cutoff values. To help identify the best cutoff to use when scoring your data, 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 0.36, where the 1-specificity value is 0.384 and the sensitivity value is 0.717.

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_acci_severity1, which is the predicted probability of the event "1" for the target acci_severity, is greater than or equal to the cutoff value. When P_acci_severity1 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

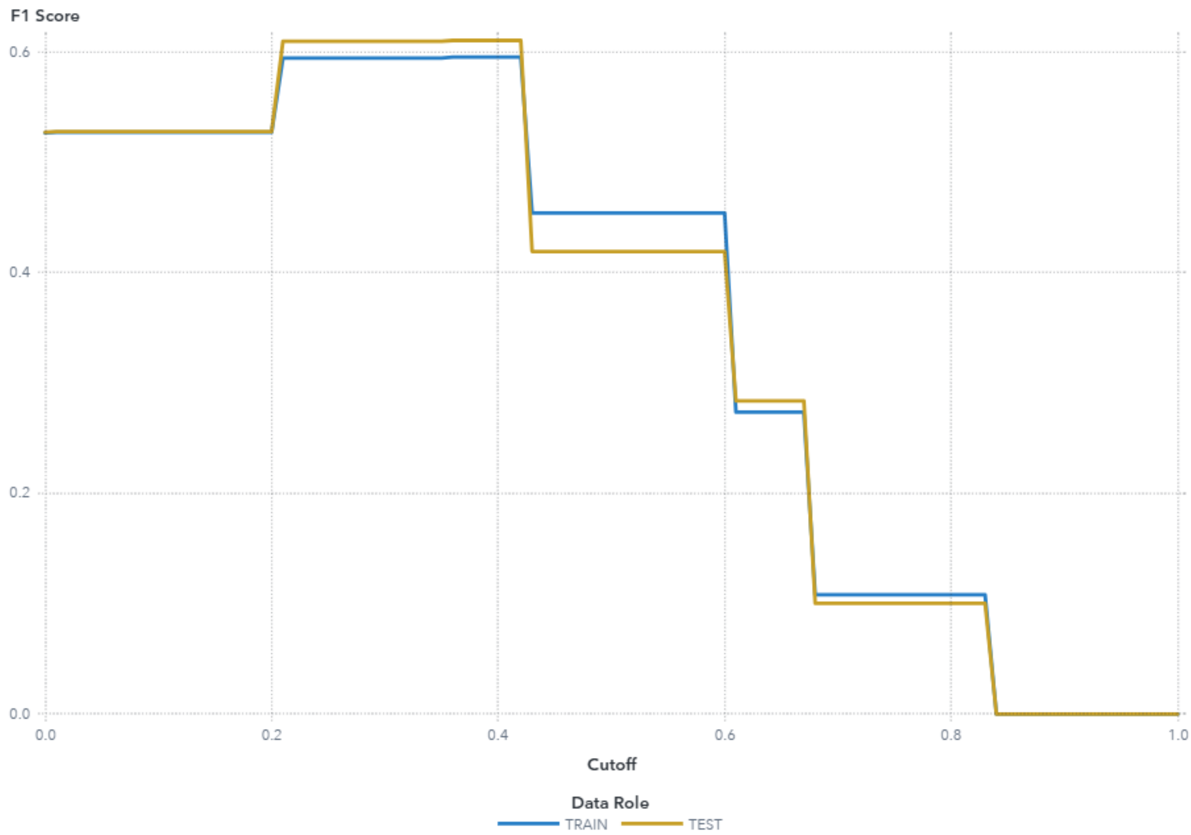


For this model, the accuracy in the TEST partition at the cutoff of 0.5 is 0.68.

For this model, the accuracy in the TRAIN partition at the cutoff of 0.5 is 0.702.

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_acci_severity1, which is the predicted probability of the event "1" for the target acci_severity, is greater than or equal to the cutoff value. When P_acci_severity1 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 TEST partition at the cutoff of 0.5 is 0.419.

For this model, the F1 score in the TRAIN partition at the cutoff of 0.5 is 0.454.

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_acci_severity1, which is the predicted probability of the event "1" for the target acci_severity, is greater than or equal to the cutoff value. When P_acci_severity1 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	Partition Indicator	Formatted Partition
acci_severity	TEST	2	2
acci_severity	TRAIN	1	1

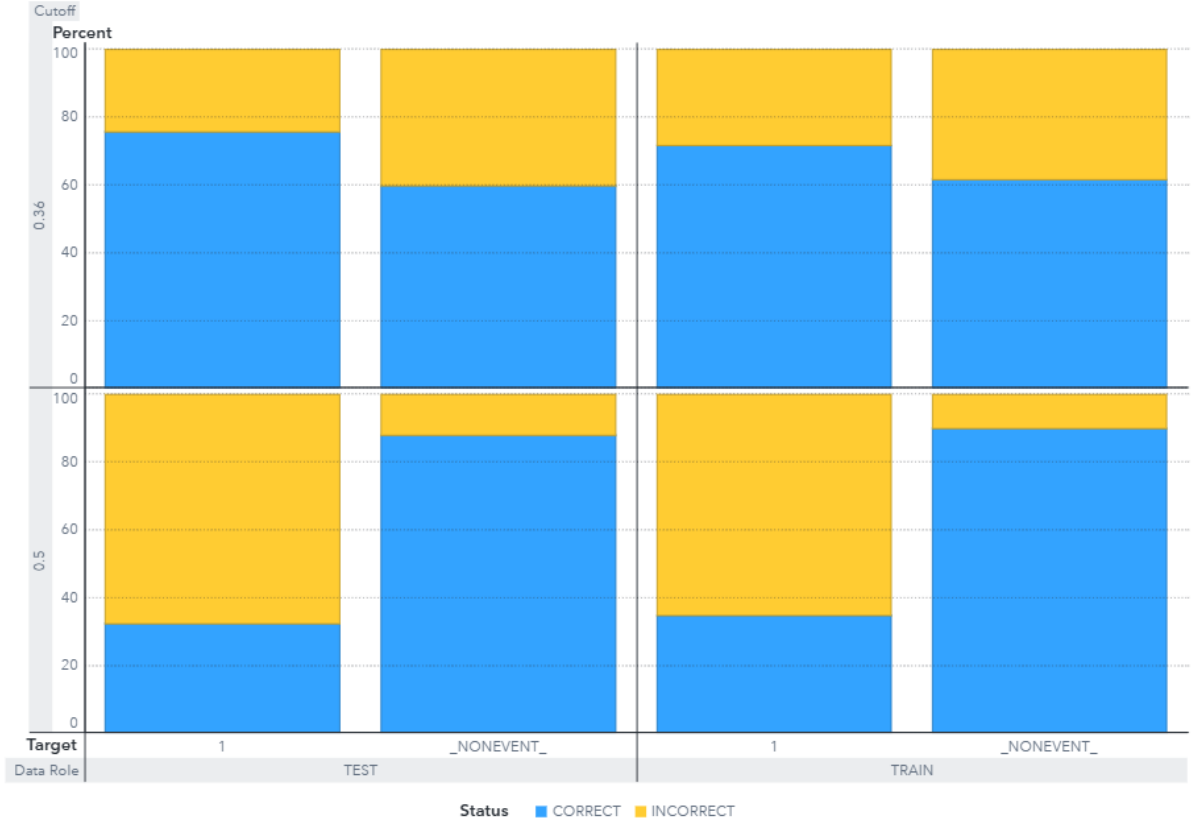
Number of Observations	Average Squared Error	Divisor for ASE	Root Average Squared Error
1,056	0.2056	1,056	0.4534
2,467	0.2054	2,467	0.4532

Misclassification Rate	Multi-Class Log Loss	KS (Youden)	Area Under ROC
0.5275	1.0232	0.3540	0.7028
0.5334	1.0237	0.3323	0.6994

Gini Coefficient	Gamma	Tau	KS Cutoff
0.4055	0.5661	0.1866	0.3600
0.3989	0.5643	0.1833	0.3600

KS at Default Cutoff	Misclassification Rate at KS Cutoff (Event)	Misclassification Rate (Event)
0.2018	0.3456	0.3201
0.2460	0.3482	0.2983

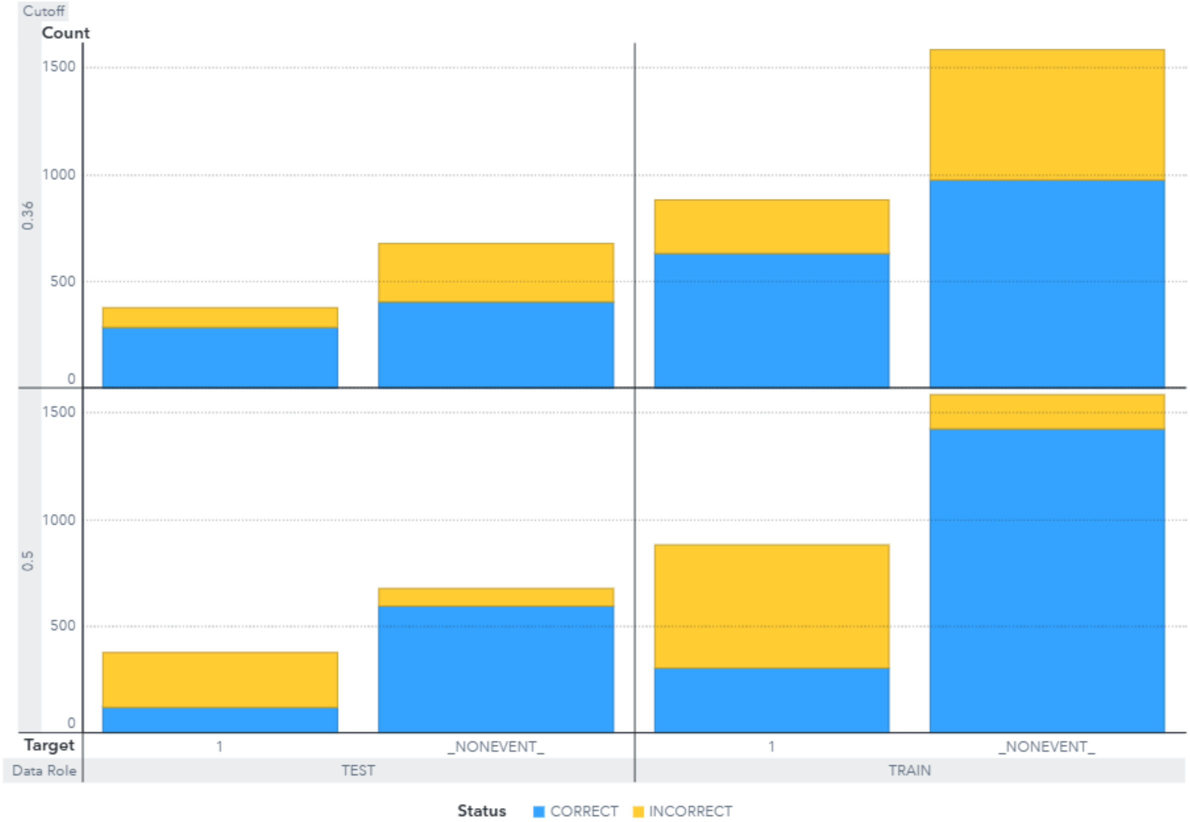
Percentage Plot



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 these KS cutoff values for existing partitions: 0.36 (TRAIN), 0.36 (TEST).

For this data, for the bar corresponding to the event level of acci_severity, "   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 these KS cutoff values for existing partitions: 0.36 (TRAIN), 0.36 (TEST).

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

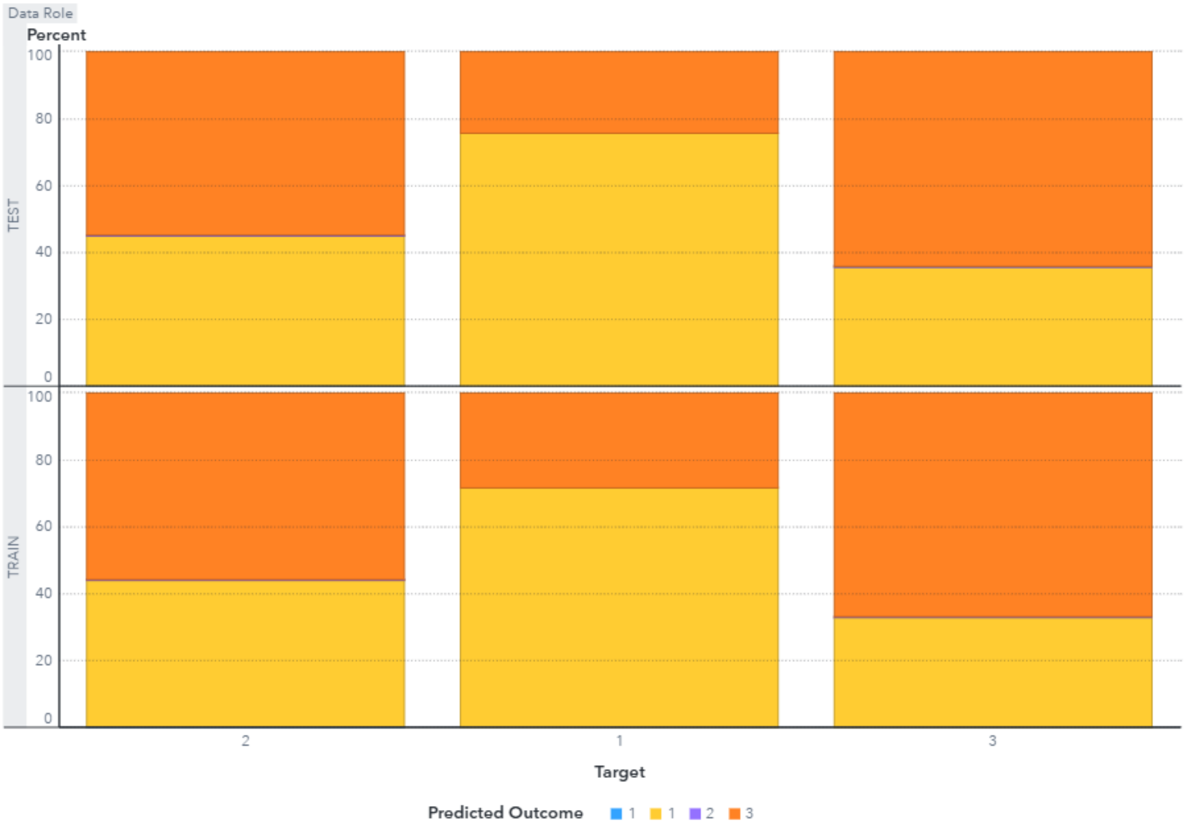
Table

Cutoff	Cutoff Source	Target Name	Response
0.3600	KS	acci_severity	CORRECT
0.3600	KS	acci_severity	INCORRECT
0.3600	KS	acci_severity	CORRECT
0.3600	KS	acci_severity	INCORRECT
0.5000	Default	acci_severity	CORRECT
0.5000	Default	acci_severity	INCORRECT
0.5000	Default	acci_severity	CORRECT
0.5000	Default	acci_severity	INCORRECT

Event	Value	Training Frequency	Validation Frequency
1	True Positive	632	
1	False Negative	250	
NONEVENT	True Negative	976	
NONEVENT	False Positive	609	
1	True Positive	306	
1	False Negative	576	
NONEVENT	True Negative	1,425	
NONEVENT	False Positive	160	

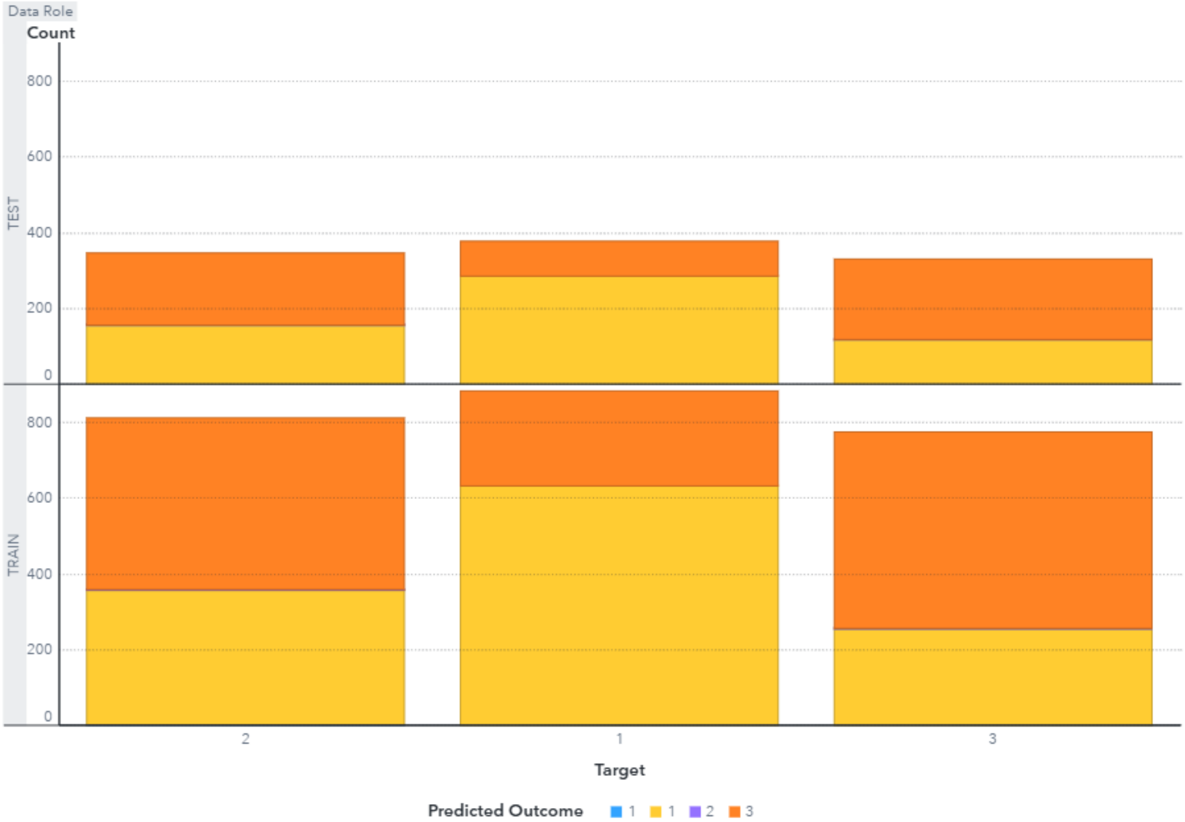
Test Frequency	Training Percentage	Validation Percentage	Test Percentage
286	71.6553		75.6614
92	28.3447		24.3386
405	61.5773		59.7345
273	38.4227		40.2655
122	34.6939		32.2751
256	65.3061		67.7249
596	89.9054		87.9056
82	10.0946		12.0944

Percentage Plot



The Nominal Classification report displays either the percentage of or the number of observations predicting each target level. The plot is segmented by target level and partition level. The target level with the greatest predicted probability is the predicted outcome. A greater number of observations where the target and predicted outcome are the same indicates a better model.

Count Plot



The Nominal Classification report displays either the percentage of or the number of observations predicting each target level. The plot is segmented by target level and partition level. The target level with the greatest predicted probability is the predicted outcome. A greater number of observations where the target and predicted outcome are the same indicates a better model.

Table

Target Name	Data Role	Target	Unformatted Target
acci_severity	TRAIN	1	1
acci_severity	TRAIN	1	1
acci_severity	TRAIN	2	2
acci_severity	TRAIN	2	2
acci_severity	TRAIN	2	2
acci_severity	TRAIN	2	2
acci_severity	TRAIN	3	3
acci_severity	TRAIN	3	3
acci_severity	TRAIN	3	3
acci_severity	TEST	1	1
acci_severity	TEST	1	1
acci_severity	TEST	2	2
acci_severity	TEST	2	2
acci_severity	TEST	2	2
acci_severity	TEST	2	2
acci_severity	TEST	3	3
acci_severity	TEST	3	3
acci_severity	TEST	3	3

Predicted Outcome	Count	Percent	Status
1	632	71.6553	CORRECT
3	250	28.3447	INCORRECT
1	3	0.3699	INCORRECT
1	354	43.6498	INCORRECT
2	2	0.2466	CORRECT
3	452	55.7337	INCORRECT
1	255	32.9457	INCORRECT
2	2	0.2584	INCORRECT
3	517	66.7959	CORRECT

Predicted Outcome	Count	Percent	Status
1	286	75.6614	CORRECT
3	92	24.3386	INCORRECT
1	1	0.2882	INCORRECT
1	155	44.6686	INCORRECT
2	1	0.2882	CORRECT
3	190	54.7550	INCORRECT
1	118	35.6495	INCORRECT
2	1	0.3021	INCORRECT
3	212	64.0483	CORRECT

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
pdPlots	false
performKernelShap	false

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

Output

The SAS System

The GENSELECT Procedure

Model Information	
Data Source	DM_AF3Z7K9DW76JQQTEWKB0AC4J2
Response Variable	acci_severity
Number of Response Levels	3
Distribution	Multinomial
Link Type	Generalized
Link Function	Logit
Optimization Technique	Newton-Raphson with Ridging
Predicted Response Level	I_acci_severity

Number of Observations

Description	Total	Training	Testing
Number of Observations Read	3523	2467	1056
Number of Observations Used	3519	2464	1055

Response Profile

Ordered Value	acci_severity	Total Frequency	Training	Testing
1	3	1105	774	331
2	2	1154	808	346
3	1	1260	882	378

Probabilities modeled use acci_severity = 1 as the reference category.

Class Level Information

Class	Levels	Values
carri_haz	5	0 1 2 3 7
first_road_class	5	1 3 4 5 6
junc_detail	9	0 1 2 3 5 6 7 8 9
loc_auth_ons_distr	11	E07000207 E07000208 E07000209 E07000210 E07000211 E07000212 E07000213 E07000214 E07000215 E07000216 E07000217
num_of_casu	8	1 2 3 4 5 6 7 9
num_of_vehi	6	1 2 3 4 5 7
ped_cross_hum_con	3	0 1 2
ped_cross_phy_facil	6	0 1 4 5 7 8
road_type	6	1 2 3 6 7 9
spec_con_site	6	0 1 3 4 5 7
speed_limit	6	20 30 40 50 60 70
time_category	4	after eveni morni night
urb_or_rur_area	2	1 2
weath_con	8	1 2 3 4 5 7 8 9

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

Selection Details

Convergence criterion (ABSGCONV=1E-7) satisfied.

Selection Summary

Step	Effect Entered	Effect Removed	Number Effects In	SBC
0	Intercept		1	5422.2064
1	num_of_vehi		2	5143.4869
2	loc_auth_ons_distr		3	4957.5827
3		loc_auth_ons_distr	2	4866.5311*

* Optimal Value Of Criterion

Stepwise selection stopped because adding or removing an effect does not improve the SBC criterion.

The model at step 3 is selected where SBC is 4866.531.

Selected Effects: Intercept num_of_vehi

Selected Model

Dimensions	
Columns in Design	14
Number of Effects	2
Max Effect Columns	12
Rank of Design	12
Parameters in Optimization	12

Fit Statistics

Description	Training	Testing
-2 Log Likelihood	5044.07049	2158.71380
AIC (smaller is better)	5068.07049	2182.71380
AICC (smaller is better)	5068.19778	2183.01323
SBC (smaller is better)	5137.78498	2242.24936
Average Square Error	0.61615	0.61676

Parameter Estimates

Parameter	acci_severity	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	3	1	8.626295	52.810402	0.0267	0.8702
Intercept	2	1	8.626295	52.810402	0.0267	0.8702
num_of_vehi 1	3	1	-9.225806	52.810484	0.0305	0.8613
num_of_vehi 1	2	1	-8.814770	52.810466	0.0279	0.8674
num_of_vehi 2	3	1	-7.899713	52.810458	0.0224	0.8811
num_of_vehi 2	2	1	-8.034073	52.810461	0.0231	0.8791
num_of_vehi 3	3	1	-9.693556	52.810638	0.0337	0.8544
num_of_vehi 3	2	1	-9.811339	52.810660	0.0345	0.8526
num_of_vehi 4	3	1	-10.378049	52.811056	0.0386	0.8442
num_of_vehi 4	2	1	-9.777275	52.810804	0.0343	0.8531
num_of_vehi 5	3	1	-10.948682	52.812481	0.0430	0.8358
num_of_vehi 5	2	1	-10.948682	52.812481	0.0430	0.8358
num_of_vehi 7	3	0	0	.	.	.
num_of_vehi 7	2	0	0	.	.	.

Score Code Variables for Predicted Probability

acci_severity	Variable
1	P_acci_severity1
3	P_acci_severity3
2	P_acci_severity2

Task Timing

Task	Seconds	Percent
Setup and Parsing	0.01	1.79%
Levelization	0.01	2.40%
Model Initialization	0.00	1.14%
SSCP Computation	0.01	2.64%
Model Selection	0.33	91.54%
Producing Score Code	0.00	0.34%
Display	0.00	0.10%
Cleanup	0.00	0.00%
Total	0.36	100.00%