



Demo

"Logistic Regression" Results

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t Values by Parameter

Parameter Estimates

Effect	Parameter	t Value	Sign
curr_days_susp	curr_days_susp	25.2901	+
handset_age_grp	handset_age_grp 24-48 Month	23.4741	+
ever_days_over_pla n	ever_days_over_pla n	18.8722	+
handset_age_grp	handset_age_grp < 24 Months	17.0484	+
avg_days_susp	avg_days_susp	15.5848	+
ever_times_over_pl an	ever_times_over_pl an	15.1087	+
calls_care_ltd	calls_care_ltd	12.4946	-
LOG_MB_Data_Us g_M08	LOG_MB_Data_Us g_M08	10.4903	+
IMP_LOG_MB_Dat a_Us g_M09	IMP_LOG_MB_Dat a_Us g_M09	8.3318	-
IMP_REP_mb_data _ndist_mo6m	IMP_REP_mb_data _ndist_mo6m	5.4203	-
LOG_MB_Data_Us g_M05	LOG_MB_Data_Us g_M05	4.3272	-
IMP_REP_mou_onn et_pct_MOM	IMP_REP_mou_onn et_pct_MOM	3.7887	+
rfm_score	rfm_score	3.2543	-
REP_calls_out_pk	REP_calls_out_pk	2.8734	-
times_susp	times_susp 0	2.5831	+
times_susp	times_susp 1	2.5002	+
LOG_MB_Data_Us g_M06	LOG_MB_Data_Us g_M06	2.2907	-
times_susp	times_susp 3	1.9779	+
times_susp	times_susp 2	1.9297	+
times_susp	times_susp 4	1.8397	+

Effect	Parameter	t Value	Sign
delinq_indicator	delinq_indicator 1	1.6775	-
delinq_indicator	delinq_indicator 0	1.3102	-
pymts_late_ltd	pymts_late_ltd 1	0.2767	-
wrk_orders	wrk_orders 5	0.2277	+
delinq_indicator	delinq_indicator 2	0.2145	+
pymts_late_ltd	pymts_late_ltd 0	0.1988	-
pymts_late_ltd	pymts_late_ltd 2	0.1864	-
pymts_late_ltd	pymts_late_ltd 5	0.1799	-
pymts_late_ltd	pymts_late_ltd 4	0.1763	-
pymts_late_ltd	pymts_late_ltd 3	0.1760	-
pymts_late_ltd	pymts_late_ltd 8	0.1743	-
pymts_late_ltd	pymts_late_ltd 6	0.1734	-
wrk_orders	wrk_orders 3	0.1717	+
pymts_late_ltd	pymts_late_ltd 7	0.1704	-
wrk_orders	wrk_orders 4	0.1688	+
wrk_orders	wrk_orders 2	0.1617	+
wrk_orders	wrk_orders 1	0.1589	+
wrk_orders	wrk_orders 0	0.1442	+
pymts_late_ltd	pymts_late_ltd 9	0.1420	-
delinq_indicator	delinq_indicator 3	0.0378	-
Intercept	Intercept	0.0182	-
REP_bill_data_usg_m03	REP_bill_data_usg_m03		+
handset_age_grp	handset_age_grp > 48 Months		+
Est_HH_Income	Est_HH_Income		+
wrk_orders	wrk_orders 7		+
wrk_orders	wrk_orders 6		+
delinq_indicator	delinq_indicator 4		+
times_susp	times_susp 6		+

Effect	Parameter	t Value	Sign
times_susp	times_susp 5		+
REP_seconds_of_data_norm	REP_seconds_of_data_norm		-
pymts_late_ltd	pymts_late_ltd 10		+
bill_data_usg_m09	bill_data_usg_m09		+
REP_mb_data_usg_roamm03	REP_mb_data_usg_roamm03		-
REP_mb_data_usg_roamm02	REP_mb_data_usg_roamm02		+
REP_bill_data_usg_m06	REP_bill_data_usg_m06		+

Estimate	Absolute Estimate	Standard Error	Chi-Square
0.1487	0.1487	0.0059	639.5902
1.4464	1.4464	0.0616	551.0340
0.0220	0.0220	0.0012	356.1583
1.0144	1.0144	0.0595	290.6478
0.0766	0.0766	0.0049	242.8851
0.1186	0.1186	0.0079	228.2715
-0.0052	0.0052	0.0004	156.1147
0.1485	0.1485	0.0142	110.0470
-0.1147	0.1147	0.0138	69.4192
-0.0508	0.0508	0.0094	29.3795
-0.0634	0.0634	0.0147	18.7243
0.0304	0.0304	0.0080	14.3541
-0.0010	0.0010	0.0003	10.5906
-0.0010	0.0010	0.0003	8.2564
2.9185	2.9185	1.1298	6.6724
2.8232	2.8232	1.1292	6.2509
-0.0312	0.0312	0.0136	5.2475

Estimate	Absolute Estimate	Standard Error	Chi-Square
2.2419	2.2419	1.1335	3.9119
2.1800	2.1800	1.1297	3.7237
2.1557	2.1557	1.1718	3.3844
-1.4088	1.4088	0.8398	2.8141
-1.0987	1.0987	0.8386	1.7167
-15.2279	15.2279	55.0330	0.0766
15.2520	15.2520	66.9697	0.0519
0.1823	0.1823	0.8496	0.0460
-10.3404	10.3404	52.0021	0.0395
-9.6948	9.6948	52.0032	0.0348
-9.3547	9.3547	52.0021	0.0324
-9.1668	9.1668	52.0021	0.0311
-9.1545	9.1545	52.0022	0.0310
-9.0657	9.0657	52.0032	0.0304
-9.0190	9.0190	52.0021	0.0301
7.2445	7.2445	42.1997	0.0295
-8.8624	8.8624	52.0022	0.0290
7.1222	7.1222	42.2035	0.0285
6.8221	6.8221	42.1993	0.0261
6.7061	6.7061	42.1992	0.0253
6.0847	6.0847	42.1992	0.0208
-7.3842	7.3842	52.0166	0.0202
-0.0338	0.0338	0.8947	0.0014
-1.2224	1.2224	66.9850	0.0003
0.0001	0.0001		
0	0		
0.0000	0.0000		
0	0		
0	0		

Estimate	Absolute Estimate	Standard Error	Chi-Square
0	0		
0	0		
0	0		
0.0000	0.0000		
0	0		
0.0000	0.0000		
-0.0001	0.0001		
0.0001	0.0001		
0.0001	0.0001		

Pr > Chi-Square	Degrees of Freedom
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0000	1
0.0002	1
0.0011	1
0.0041	1
0.0098	1
0.0124	1
0.0220	1
0.0479	1

Pr > Chi-Square	Degrees of Freedom
0.0536	1
0.0658	1
0.0934	1
0.1901	1
0.7820	1
0.8198	1
0.8301	1
0.8424	1
0.8521	1
0.8572	1
0.8601	1
0.8603	1
0.8616	1
0.8623	1
0.8637	1
0.8647	1
0.8660	1
0.8716	1
0.8737	1
0.8853	1
0.8871	1
0.9699	1
0.9854	1
	0
	0
	0
	0
	0

Selection Summary

Step	Effect Entered	Number of Effects	SBC
0	Intercept	1	29,271.0671
1	curr_days_susp	2	23,530.6099
2	handset_age_grp	3	22,407.3798
3	ever_days_over_pla n	4	21,290.3451
4	pymts_late_ltd	5	20,924.2270
5	avg_days_susp	6	20,464.5240
6	REP_seconds_of_d ata_norm	7	20,253.8666
7	ever_times_over_pl an	8	19,964.9584
8	times_susp	9	19,776.7970
9	wrk_orders	10	19,652.7933
10	calls_care_ltd	11	19,546.1725
11	delinq_indicator	12	19,466.6869
12	IMP_LOG_MB_Dat a_Usg_M09	13	19,437.9120
13	LOG_MB_Data_Us g_M08	14	19,360.3081
14	LOG_MB_Data_Us g_M05	15	19,330.6152
15	IMP_REP_mb_data _ndist_mo6m	16	19,314.2573
16	IMP_REP_mou_onn et_pct_MOM	17	19,302.4954
17	REP_bill_data_usg _m06	18	19,297.5455
18	REP_bill_data_usg _m03	19	19,285.9992
19	rfm_score	20	19,271.7257

Step	Effect Entered	Number of Effects	SBC
20	bill_data_usg_m09	21	19,272.0366
21	REP_calls_out_pk	22	19,266.1174
22	Est_HH_Income	23	19,270.5180
23	REP_mb_data_usg _roamm03	24	19,265.1091
24	REP_mb_data_usg _roamm02	25	19,256.5915
25	LOG_MB_Data_Us g_M06	26	19,252.0254
26	mfg_apple	27	19,257.4759
27	open_tsupcomplnts	28	19,264.6539
28	res_calls_6mavg_ac ct	29	19,272.5445

[illegible]

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

Regression Fit Statistics

Statistic	Description	Training	Validation
M2LL	-2 Log Likelihood	18,817.9986	8,072.8809
AIC	AIC (smaller is better)	18,899.9986	8,154.8809
AICC	AICC (smaller is better)	18,900.0857	8,155.0844
SBC	SBC (smaller is better)	19,252.0382	8,472.1809
ASE	Average Square Error	0.0599	0.0598

Score Inputs

Name	Role	Variable Level	Type
avg_arpu_3m	INPUT	INTERVAL	N
avg_data_chrgs_3m	INPUT	INTERVAL	N
avg_data_prem_chrgs_3m	INPUT	INTERVAL	N
avg_days_susp	INPUT	INTERVAL	N
avg_overage_chrgs_3m	INPUT	INTERVAL	N
bill_data_usg_m03	INPUT	INTERVAL	N
bill_data_usg_m06	INPUT	INTERVAL	N
bill_data_usg_m09	INPUT	INTERVAL	N
calls_care_ltd	INPUT	INTERVAL	N
calls_in_offpk	INPUT	INTERVAL	N
calls_in_pk	INPUT	INTERVAL	N
calls_out_offpk	INPUT	INTERVAL	N
calls_out_pk	INPUT	INTERVAL	N
calls_total	INPUT	INTERVAL	N
cs_afr_amer	INPUT	INTERVAL	N
cs_caucasian	INPUT	INTERVAL	N
cs_hispanic	INPUT	INTERVAL	N
cs_med_home_value	INPUT	INTERVAL	N
cs_other	INPUT	INTERVAL	N
cs_pct_home_owner	INPUT	INTERVAL	N
cs_ttl_female	INPUT	INTERVAL	N
cs_ttl_hhlds	INPUT	INTERVAL	N
cs_ttl_male	INPUT	INTERVAL	N
cs_ttl_mdage	INPUT	INTERVAL	N
cs_ttl_pop	INPUT	INTERVAL	N

Name	Role	Variable Level	Type
cs_ttl_rural	INPUT	INTERVAL	N
cs_ttl_urban	INPUT	INTERVAL	N
curr_days_susp	INPUT	INTERVAL	N
data_device_age	INPUT	INTERVAL	N
data_prem_chrgs_curr	INPUT	INTERVAL	N
delinq_indicator	INPUT	NOMINAL	N
Est_HH_Income	INPUT	INTERVAL	N
ever_days_over_plan	INPUT	INTERVAL	N
ever_times_over_plan	INPUT	INTERVAL	N
handset_age_grp	INPUT	NOMINAL	C
lifetime_value	INPUT	INTERVAL	N
mb_data_ndist_mom6m	INPUT	INTERVAL	N
mb_data_usg_m01	INPUT	INTERVAL	N
mb_data_usg_m02	INPUT	INTERVAL	N
mb_data_usg_m03	INPUT	INTERVAL	N
MB_Data_Usg_M04	INPUT	INTERVAL	N
MB_Data_Usg_M05	INPUT	INTERVAL	N
MB_Data_Usg_M06	INPUT	INTERVAL	N
MB_Data_Usg_M07	INPUT	INTERVAL	N
MB_Data_Usg_M08	INPUT	INTERVAL	N
MB_Data_Usg_M09	INPUT	INTERVAL	N
mb_data_usg_roamm01	INPUT	INTERVAL	N
mb_data_usg_roamm02	INPUT	INTERVAL	N
mb_data_usg_roamm03	INPUT	INTERVAL	N

Name	Role	Variable Level	Type
mou_onnet_pct_MOM	INPUT	INTERVAL	N
mou_total_pct_MOM	INPUT	INTERVAL	N
nbr_data_cdrs	INPUT	INTERVAL	N
pymts_late_ltd	INPUT	NOMINAL	N
rfm_score	INPUT	INTERVAL	N
seconds_of_data_logging	INPUT	INTERVAL	N
seconds_of_data_norm	INPUT	INTERVAL	N
times_susp	INPUT	NOMINAL	N
tot_drpd_pr1	INPUT	INTERVAL	N
tot_mb_data_curr	INPUT	INTERVAL	N
tot_mb_data_roam_curr	INPUT	INTERVAL	N
tot_overage_chgs	INPUT	INTERVAL	N
tot_voice_chrgs_curr	INPUT	INTERVAL	N
voice_tot_bill_mou_curr	INPUT	INTERVAL	N
wrk_orders	INPUT	NOMINAL	N

Variable Type	Variable Label	Variable Format	Variable Length
double	3M Avg Revenue per User	DOLLAR8.2	8
double	3M Avg Data Charges	DOLLAR8.2	8
double	3M Avg Premium Data Charges	DOLLAR8.2	8
double	Days Suspended Last 6M	BEST2.0	8

Variable Type	Variable Label	Variable Format	Variable Length
double	3M Avg Overage Charges	DOLLAR8.2	8
double	3M Avg Billed Data Usage	COMMA8.0	8
double	6M Avg Billed Data Usage	COMMA8.0	8
double	9M Avg Billed Data Usage	COMMA8.0	8
double	Total Calls to Care Lifetime	BEST12.0	8
double	Calls Incoming Off-Peak	COMMA8.0	8
double	Calls Incoming Peak	COMMA8.0	8
double	Calls Outgoing Off-Peak	COMMA8.0	8
double	Calls Outgoing Peak	COMMA8.0	8
double	Total Calls Curr	COMMA8.0	8
double	Census Area African-American	BEST8.3	8
double	Census Area Caucasian	BEST8.3	8
double	Census Area Hispanic	BEST8.3	8
double	Census Area Median Home Value Index	BEST4.2	8
double	Census Area Other	BEST8.3	8
double	Census Area Percent Home Owner	BEST8.3	8
double	Census Area Total	BEST8.3	8

Variable Type	Variable Label	Variable Format	Variable Length
	Female		
double	Census Area Total Households	COMMA12.0	8
double	Census Area Total Males	BEST8.3	8
double	Census Area Median Age	BEST3.0	8
double	Census Area Total Population	COMMA12.0	8
double	Census Area Total Rural	BEST8.3	8
double	Census Area Total Urban	BEST8.3	8
double	Number of Days Suspended	BEST4.0	8
double	Avg Age of Devices on Plan	COMMA10.0	8
double	Premium Data Charges	DOLLAR8.2	8
double	Delinquent Indicator	BEST2.0	8
double	Estimated HH Income	DOLLAR8.0	8
double	Total Days Over Plan	BEST2.0	8
double	Total Times Over Plan	BEST2.0	8
char	Handset Age Group	\$CHAR12.	12
double	Lifetime Value	DOLLAR8.2	8
double	6M Avg Billed Data Usage Normally Distributed	BEST12.0	8
double	MB Data Usage 1 Mth Prior	COMMA8.0	8

Variable Type	Variable Label	Variable Format	Variable Length
double	MB Data Usage 2 Mths Prior	COMMA8.0	8
double	MB Data Usage 3 Mths Prior	COMMA8.0	8
double	MB of Data Usage Month 4	BEST12.0	8
double	MB of Data Usage Month 5	BEST12.0	8
double	MB of Data Usage Month 6	BEST12.0	8
double	MB of Data Usage Month 7	BEST12.0	8
double	MB of Data Usage Month 8	BEST12.0	8
double	MB of Data Usage Month 9	BEST12.0	8
double	MB Data Usage Roam 1 Mth Prior	COMMA8.0	8
double	MB Data Usage Roam 2 Mths Prior	COMMA8.0	8
double	MB Data Usage Roam 3 Mths Prior	COMMA8.0	8
double	Minutes On Network Pct Change Month over Month	PERCENT8.2	8
double	Minutes Total Pct Change Month over Month	PERCENT8.2	8
double	Number of Data Records	COMMA10.0	8
double	Total Late Payments Lifetime	BEST2.0	8

Variable Type	Variable Label	Variable Format	Variable Length
double	Account Ranking (RFM Score)	BEST3.0	8
double	Seconds of Data - Natural Log		8
double	Seconds of Data - Normalized		8
double	Number of Times Suspended	BEST4.0	8
double	Number of Dropped Calls 1 Mth Prior	COMMA8.0	8
double	Total MB of Data Usage	COMMA8.0	8
double	Total MB of Roam Data Usage	COMMA8.0	8
double	Total Overage Charges	DOLLAR8.2	8
double	Total Voice Charges	DOLLAR8.2	8
double	Total Voice Billed Minutes of Use	COMMA8.0	8
double	Open Work Orders	BEST8.0	8

Score Outputs

Name	Role	Type	Variable Type
EM_CLASSIFICATION	CLASSIFICATION	C	char
EM_EVENTPROBABILITY	PREDICT	N	double
EM_PROBABILITY	PREDICT	N	double
IMP_LOG_MB_Data_Usg_M09	INPUT	N	double
IMP_REP_data_device_age	INPUT	N	double
IMP_REP_mb_data_ndist_mo6m	INPUT	N	double
IMP_REP_mou_onnet_pct_MOM	INPUT	N	double
IMP_REP_mou_total_pct_MOM	INPUT	N	double
IMP_avg_arpu_3m	INPUT	N	double
IMP_avg_data_chrgs_3m	INPUT	N	double
IMP_avg_data_prem_chrgs_3m	INPUT	N	double
IMP_avg_ouverage_chrgs_3m	INPUT	N	double
IMP_cs_afr_amer	INPUT	N	double
IMP_cs_caucasian	INPUT	N	double
IMP_cs_hispanic	INPUT	N	double
IMP_cs_med_home_value	INPUT	N	double
IMP_cs_other	INPUT	N	double
IMP_cs_pct_home_owner	INPUT	N	double
IMP_cs_ttl_female	INPUT	N	double

Name	Role	Type	Variable Type
IMP_cs_ttl_hhlds	INPUT	N	double
IMP_cs_ttl_male	INPUT	N	double
IMP_cs_ttl_mdage	INPUT	N	double
IMP_cs_ttl_pop	INPUT	N	double
IMP_cs_ttl_rural	INPUT	N	double
IMP_cs_ttl_urban	INPUT	N	double
IMP_data_prem_chrgs_curr	INPUT	N	double
IMP_nbr_data_cdrs	INPUT	N	double
IMP_seconds_of_data_log	INPUT	N	double
IMP_tot_drpd_pr1	INPUT	N	double
IMP_tot_overage_chgs	INPUT	N	double
IMP_tot_voice_chrgs_curr	INPUT	N	double
I_churn	CLASSIFICATION	C	char
LOG_MB_Data_Us_g_M04	INPUT	N	double
LOG_MB_Data_Us_g_M05	INPUT	N	double
LOG_MB_Data_Us_g_M06	INPUT	N	double
LOG_MB_Data_Us_g_M07	INPUT	N	double
LOG_MB_Data_Us_g_M08	INPUT	N	double
LOG_MB_Data_Us_g_M09	REJECTED	N	double
P_churn0	PREDICT	N	double
P_churn1	PREDICT	N	double
REP_bill_data_usg	INPUT	N	double

Name	Role	Type	Variable Type
_m03			
REP_bill_data_usg_m06	INPUT	N	double
REP_calls_in_offpk	INPUT	N	double
REP_calls_in_pk	INPUT	N	double
REP_calls_out_offpk	INPUT	N	double
REP_calls_out_pk	INPUT	N	double
REP_calls_total	INPUT	N	double
REP_data_device_age	REJECTED	N	double
REP_lifetime_value	INPUT	N	double
REP_mb_data_ndist_mo6m	REJECTED	N	double
REP_mb_data_usg_m01	INPUT	N	double
REP_mb_data_usg_m02	INPUT	N	double
REP_mb_data_usg_m03	INPUT	N	double
REP_mb_data_usg_roamm01	INPUT	N	double
REP_mb_data_usg_roamm02	INPUT	N	double
REP_mb_data_usg_roamm03	INPUT	N	double
REP_mou_onnet_pct_MOM	REJECTED	N	double
REP_mou_total_pct_MOM	REJECTED	N	double
REP_seconds_of_data_norm	INPUT	N	double

Name	Role	Type	Variable Type
REP_tot_mb_data_curr	INPUT	N	double
REP_tot_mb_data_roam_curr	INPUT	N	double
REP_voice_tot_bill_mou_curr	INPUT	N	double

Variable Label	Variable Format	Variable Length	Creator
Predicted for churn		2	logisticreg
Probability for churn=1		8	logisticreg
Probability of Classification		8	logisticreg
Imputed Transformed MB of Data Usage Month 9		8	impute
Imputed Replacement: Avg Age of Devices on Plan	COMMA10.0	8	impute
Imputed Replacement: 6M Avg Billed Data Usage Normally Distributed	BEST12.0	8	impute
Imputed Replacement: Minutes On Network Pct Change Month over Month	PERCENT8.2	8	impute
Imputed Replacement: Minutes Total Pct	PERCENT8.2	8	impute

Variable Label	Variable Format	Variable Length	Creator
Change Month over Month			
Imputed 3M Avg Revenue per User	DOLLAR8.2	8	impute
Imputed 3M Avg Data Charges	DOLLAR8.2	8	impute
Imputed 3M Avg Premium Data Charges	DOLLAR8.2	8	impute
Imputed 3M Avg Overage Charges	DOLLAR8.2	8	impute
Imputed Census Area African-American	BEST8.3	8	impute
Imputed Census Area Caucasian	BEST8.3	8	impute
Imputed Census Area Hispanic	BEST8.3	8	impute
Imputed Census Area Median Home Value Index	BEST4.2	8	impute
Imputed Census Area Other	BEST8.3	8	impute
Imputed Census Area Percent Home Owner	BEST8.3	8	impute
Imputed Census Area Total Female	BEST8.3	8	impute
Imputed Census Area Total Households	COMMA12.0	8	impute
Imputed Census Area Total Males	BEST8.3	8	impute
Imputed Census	BEST3.0	8	impute

Variable Label	Variable Format	Variable Length	Creator
Area Median Age			
Imputed Census Area Total Population	COMMA12.0	8	impute
Imputed Census Area Total Rural	BEST8.3	8	impute
Imputed Census Area Total Urban	BEST8.3	8	impute
Imputed Premium Data Charges	DOLLAR8.2	8	impute
Imputed Number of Data Records	COMMA10.0	8	impute
Imputed Seconds of Data - Natural Log		8	impute
Imputed Number of Dropped Calls 1 Mth Prior	COMMA8.0	8	impute
Imputed Total Overage Charges	DOLLAR8.2	8	impute
Imputed Total Voice Charges	DOLLAR8.2	8	impute
Into: churn		2	logisticreg
Transformed MB of Data Usage Month 4		8	transform
Transformed MB of Data Usage Month 5		8	transform
Transformed MB of Data Usage Month 6		8	transform
Transformed MB of Data Usage Month 7		8	transform

Variable Label	Variable Format	Variable Length	Creator
Transformed MB of Data Usage Month 8		8	transform
Transformed MB of Data Usage Month 9		8	transform
Predicted: churn=0		8	logisticreg
Predicted: churn=1		8	logisticreg
Replacement: 3M Avg Billed Data Usage	COMMA8.0	8	replacement
Replacement: 6M Avg Billed Data Usage	COMMA8.0	8	replacement
Replacement: Calls Incoming Off-Peak	COMMA8.0	8	replacement
Replacement: Calls Incoming Peak	COMMA8.0	8	replacement
Replacement: Calls Outgoing Off-Peak	COMMA8.0	8	replacement
Replacement: Calls Outgoing Peak	COMMA8.0	8	replacement
Replacement: Total Calls Curr	COMMA8.0	8	replacement
Replacement: Avg Age of Devices on Plan	COMMA10.0	8	replacement
Replacement: Lifetime Value	DOLLAR8.2	8	replacement
Replacement: 6M Avg Billed Data Usage Normally Distributed	BEST12.0	8	replacement
Replacement: MB	COMMA8.0	8	replacement

Variable Label	Variable Format	Variable Length	Creator
Data Usage 1 Mth Prior			
Replacement: MB Data Usage 2 Mths Prior	COMMA8.0	8	replacement
Replacement: MB Data Usage 3 Mths Prior	COMMA8.0	8	replacement
Replacement: MB Data Usage Roam 1 Mth Prior	COMMA8.0	8	replacement
Replacement: MB Data Usage Roam 2 Mths Prior	COMMA8.0	8	replacement
Replacement: MB Data Usage Roam 3 Mths Prior	COMMA8.0	8	replacement
Replacement: Minutes On Network Pct Change Month over Month	PERCENT8.2	8	replacement
Replacement: Minutes Total Pct Change Month over Month	PERCENT8.2	8	replacement
Replacement: Seconds of Data - Normalized		8	replacement
Replacement: Total MB of Data Usage	COMMA8.0	8	replacement
Replacement: Total MB of Roam Data Usage	COMMA8.0	8	replacement
Replacement: Total	COMMA8.0	8	replacement

Variable Label	Variable Format	Variable Length	Creator
Voice Billed Minutes of Use			

[illegible]

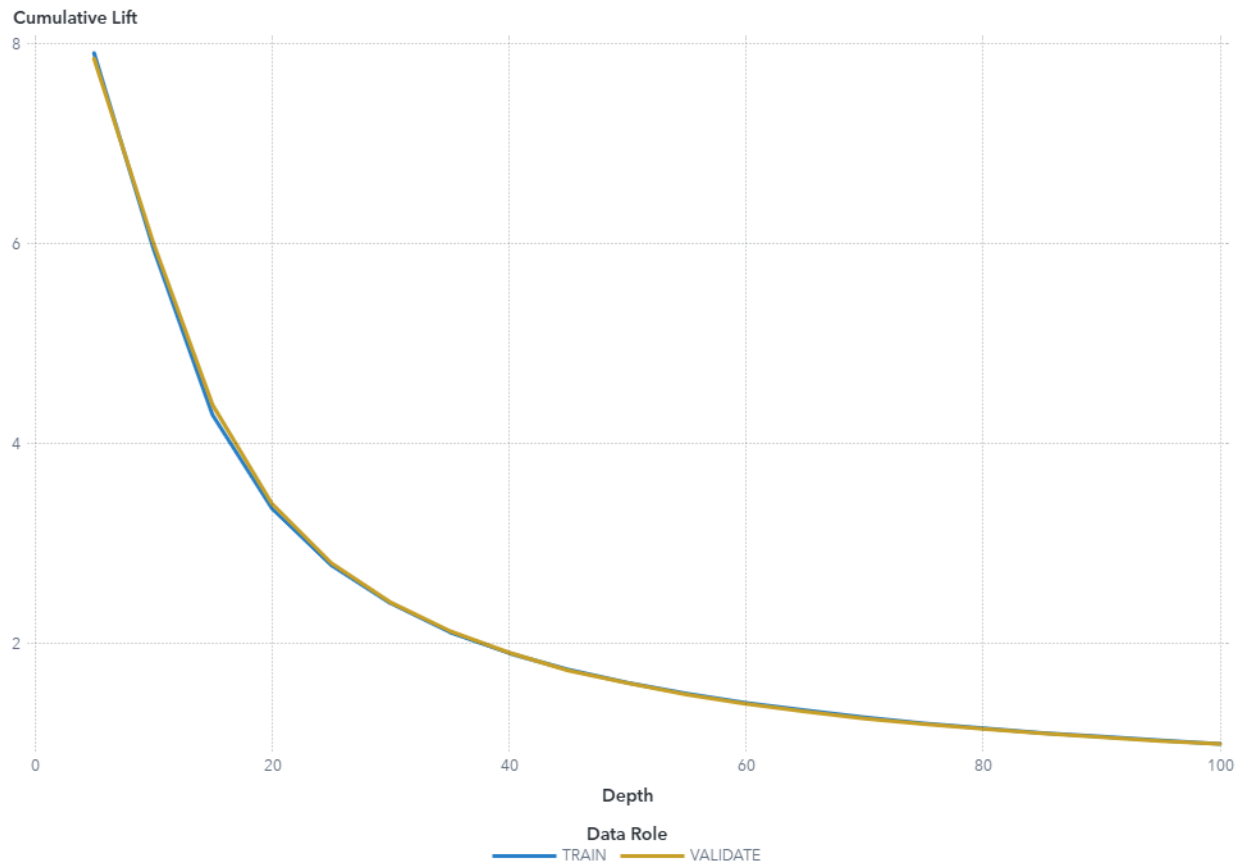
[illegible]

Function	Creator GUID
	a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
TRANSFORM	907a829f-c39c-4442-9da4-a51e2549996f
CLASSIFICATION	557d2d98-4dd5-44f5-9dd6-88e517f5b7ae
TRANSFORM	7cd5f313-cfef-45df-abd8-746010ad74d4

Function	Creator GUID
TRANSFORM	7cd5f313-cfef-45df-abd8-746010ad74d4
TRANSFORM	7cd5f313-cfef-45df-abd8-746010ad74d4
TRANSFORM	7cd5f313-cfef-45df-abd8-746010ad74d4
TRANSFORM	7cd5f313-cfef-45df-abd8-746010ad74d4
TRANSFORM	7cd5f313-cfef-45df-abd8-746010ad74d4
PREDICT	557d2d98-4dd5-44f5-9dd6-88e517f5b7ae
PREDICT	557d2d98-4dd5-44f5-9dd6-88e517f5b7ae
TRANSFORM	2c293f10-115e-4978-9f1d-0a2aa860a950
TRANSFORM	2c293f10-115e-4978-9f1d-0a2aa860a950
TRANSFORM	2c293f10-115e-4978-9f1d-0a2aa860a950
TRANSFORM	2c293f10-115e-4978-9f1d-0a2aa860a950
TRANSFORM	2c293f10-115e-4978-9f1d-0a2aa860a950

[illegible]

Cumulative Lift



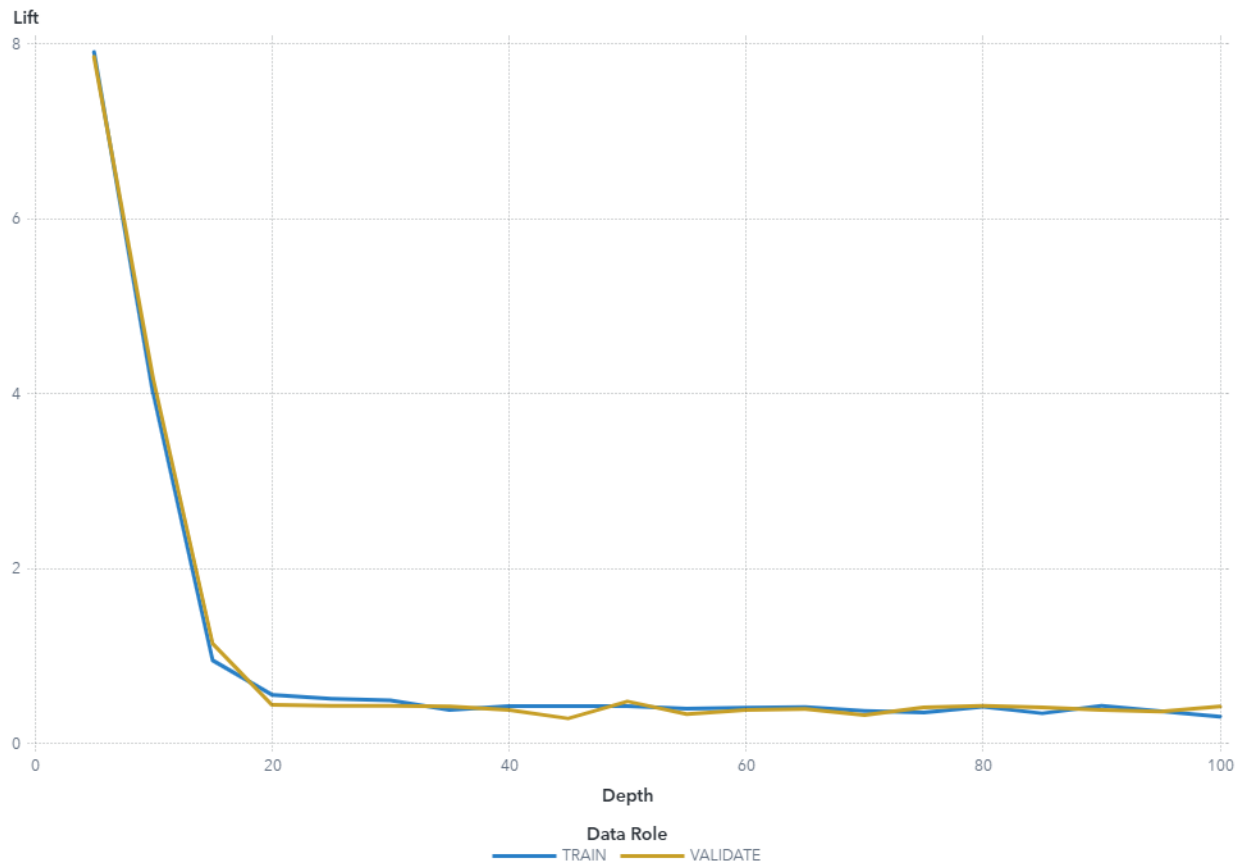
The VALIDATE partition has a Cumulative Lift of 6.01 in the 10% quantile (depth of 10) meaning there are 6.01 times more events in the first two quantiles than expected by random (10% of the total number of events). Because this value is greater than 1, it is better to use your model to identify responders than no model, based on the selected partition.

The TRAIN partition has a Cumulative Lift of 5.95 in the 10% quantile (depth of 10) meaning there are 5.95 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_churn1`, which represents the predicted probability of the event "1" for the target churn. 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



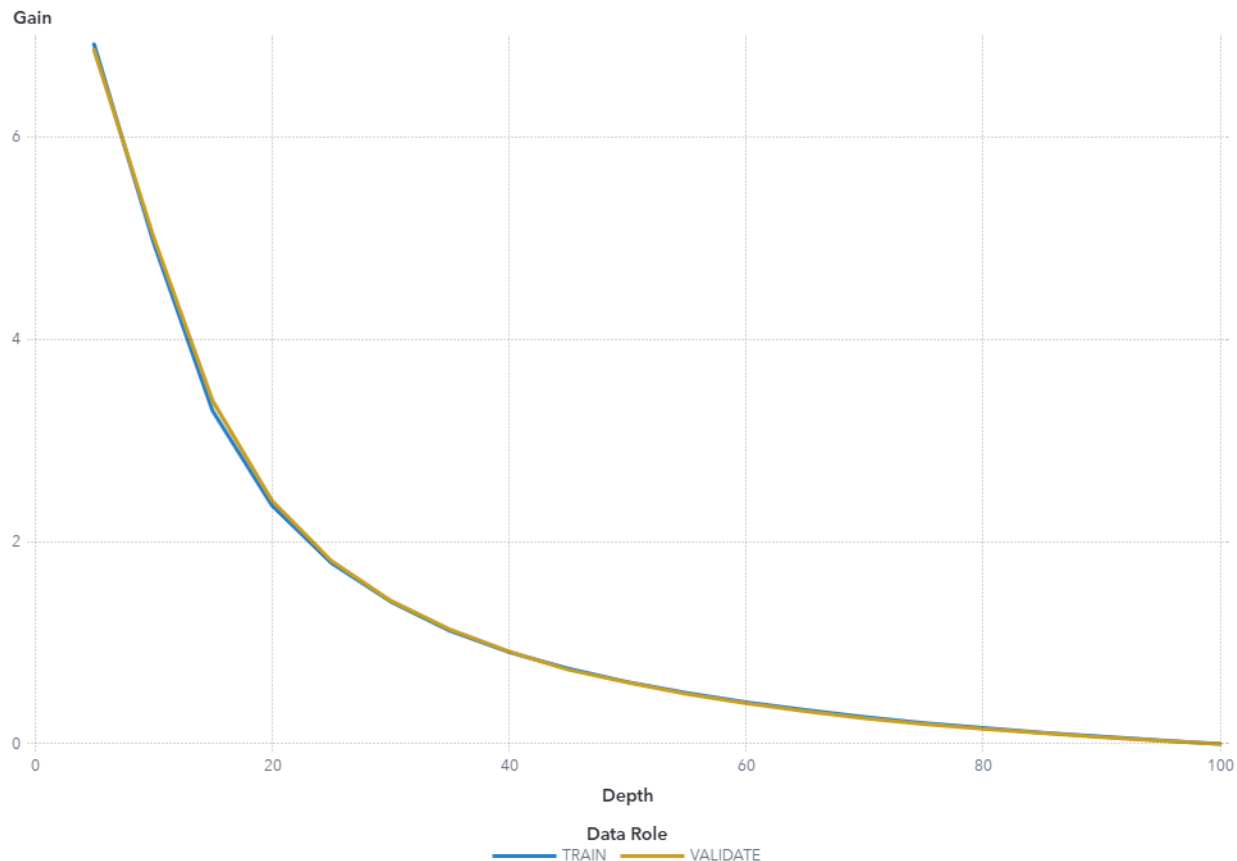
The VALIDATE partition has a Lift of 7.86 in the 5% quantile (depth of 5) meaning there are 7.86 times more events in that quantile than expected by random (5% of the total number of events). Because this value is greater than 1, it is better to use your model to identify responders than no model, based on the selected partition.

The TRAIN partition has a Lift of 7.91 in the 5% quantile (depth of 5) meaning there are 7.91 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_{churn1} , which represents the predicted probability of the event "1" for the target churn. 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



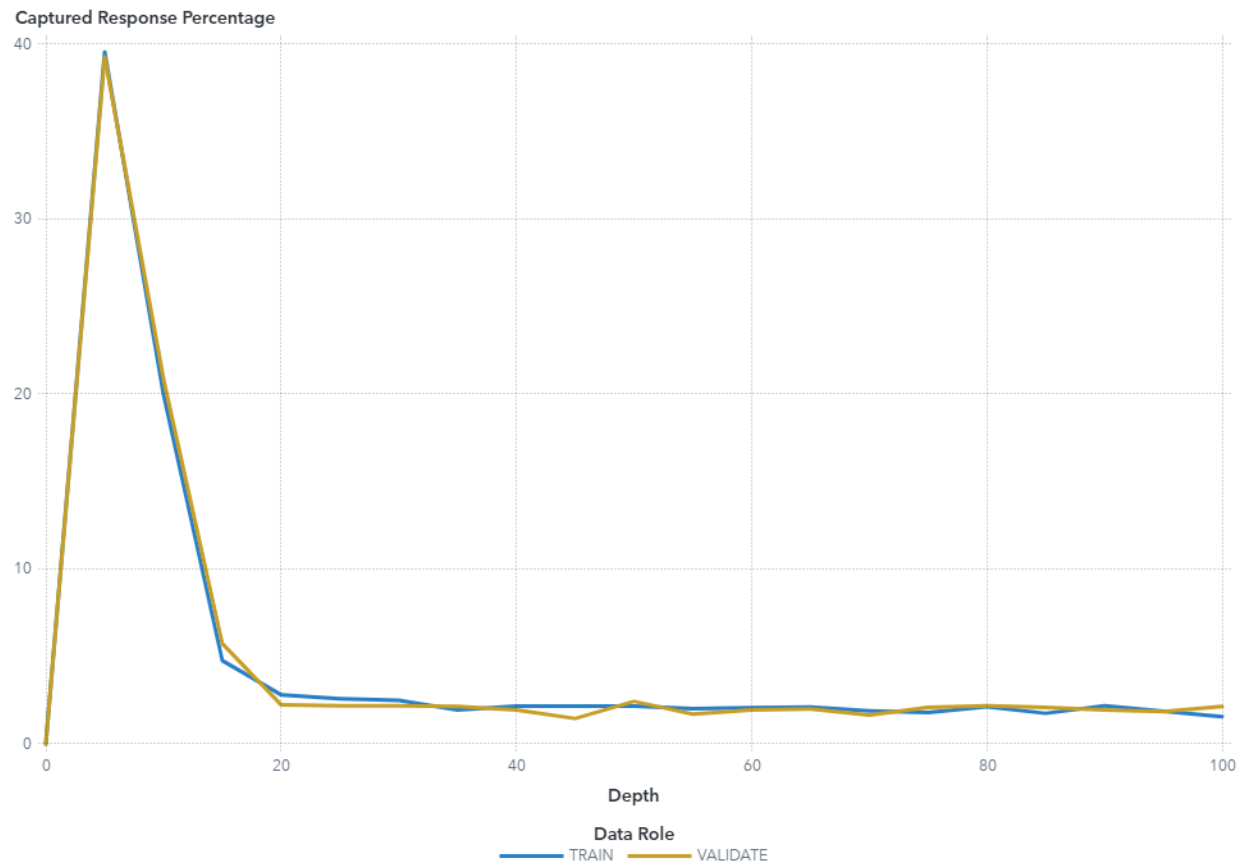
The VALIDATE partition has a Gain of 5 at the 10% quantile (depth of 10). Because this value is greater than 0, it is better to use your model to identify responders than no model, based on the selected partition. The best possible value of Gain for this partition at depth 10 is 7.25.

The TRAIN partition has a Gain of 5 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 7.24.

Gain is calculated by sorting each partition in descending order by the predicted probability of the target event P_{churn1} , which represents the predicted probability of the event "1" for the target churn. 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 and including the current one and is calculated as $(\text{number of events in the quantiles}) / (\text{number of events expected by random}) - 1$. 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

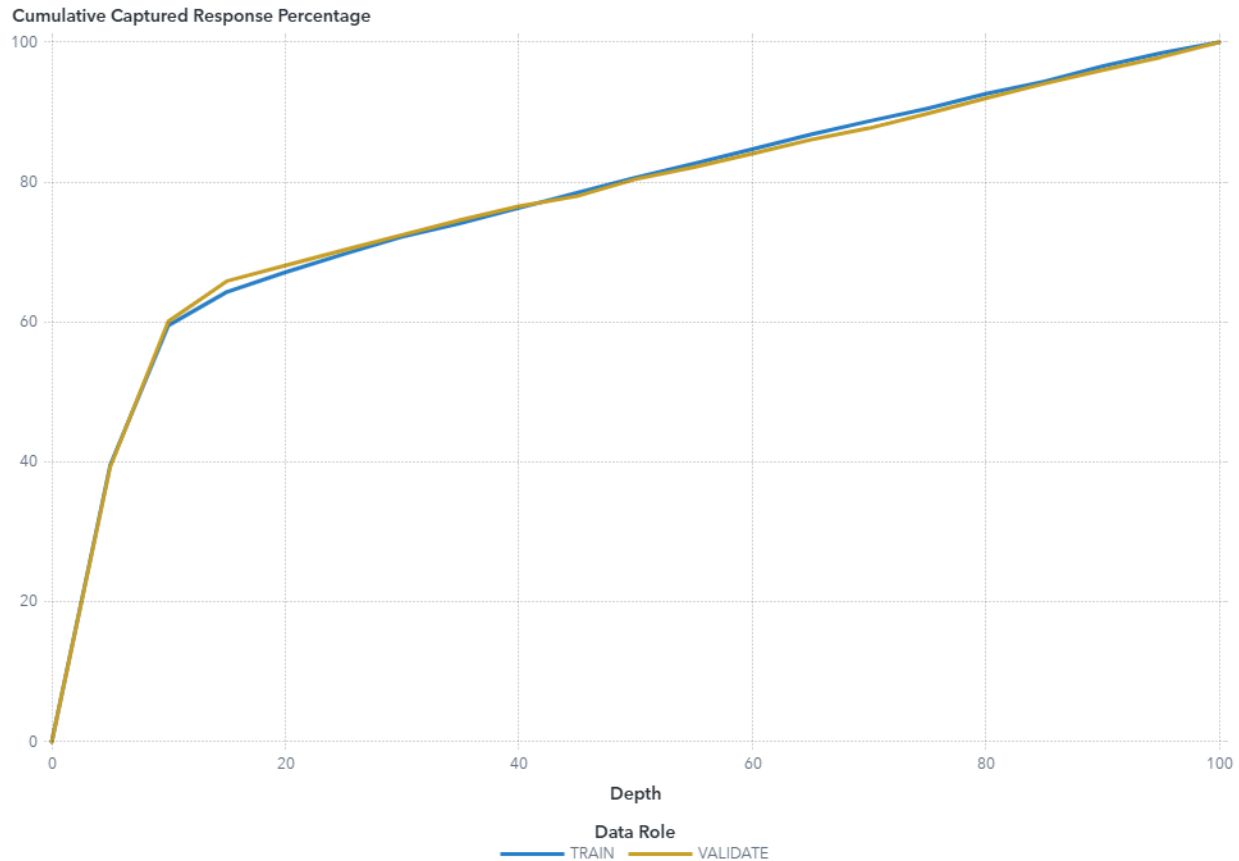


At the 5% quantile (depth of 5), the VALIDATE partition has a Captured response percentage of 39.3 (compared to the expected value of 5 for no model). The best possible value of Captured response percentage for this partition at depth 5 is 41.23.

At the 5% quantile (depth of 5), the TRAIN partition has a Captured response percentage of 39.6 (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 41.22.

Captured response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_{churn1} , which represents the predicted probability of the event "1" for the target churn. 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



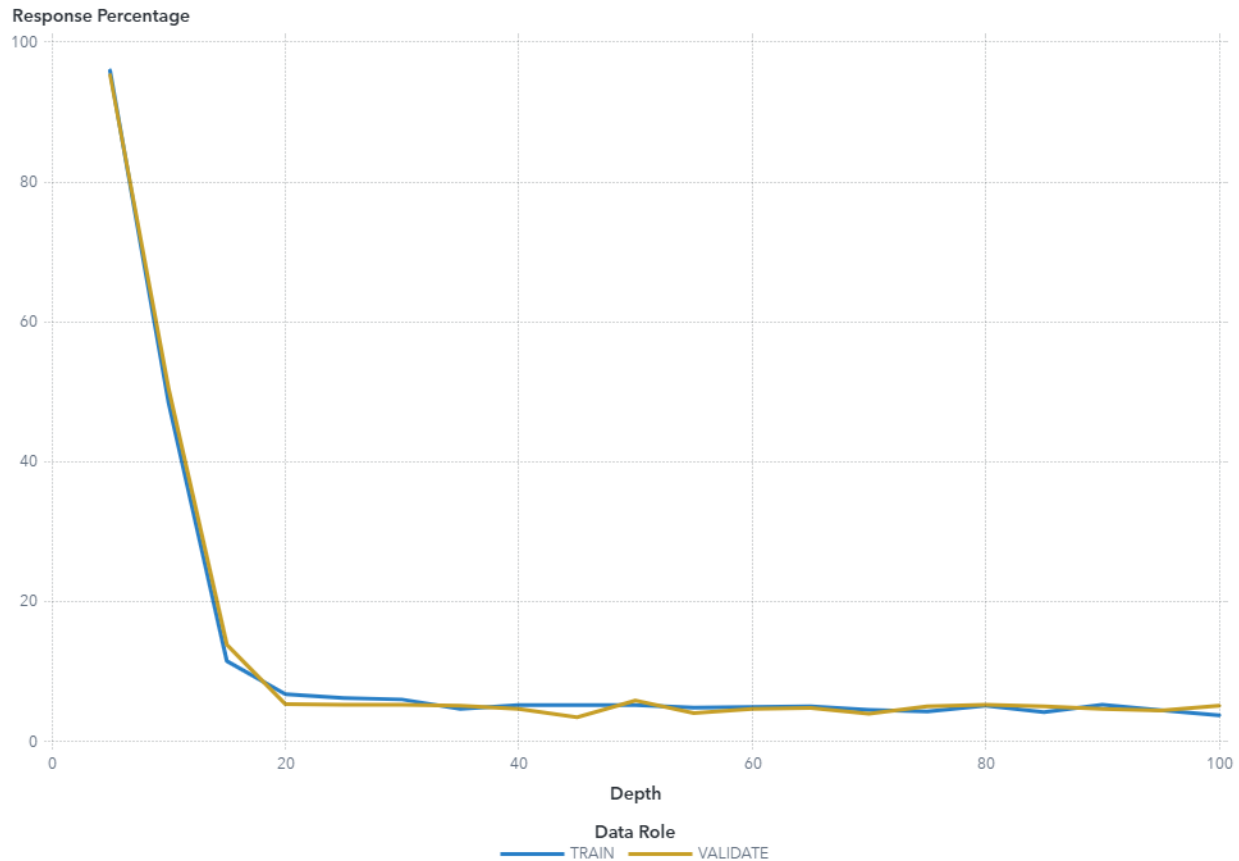
In the top 10% of the data (depth 10), the VALIDATE partition has a Cumulative captured response percentage of 60.1 (compared to the expected value of 10 for no model). The best possible value of Cumulative captured response percentage for this partition at depth 10 is 82.47.

In the top 10% of the data (depth 10), the TRAIN partition has a Cumulative captured response percentage of 59.5 (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 82.45.

Cumulative captured response percentage is calculated by sorting each partition in descending order by the predicted probability of the target event P_{churn1} , which represents the predicted probability of the event "1" for the target churn. 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

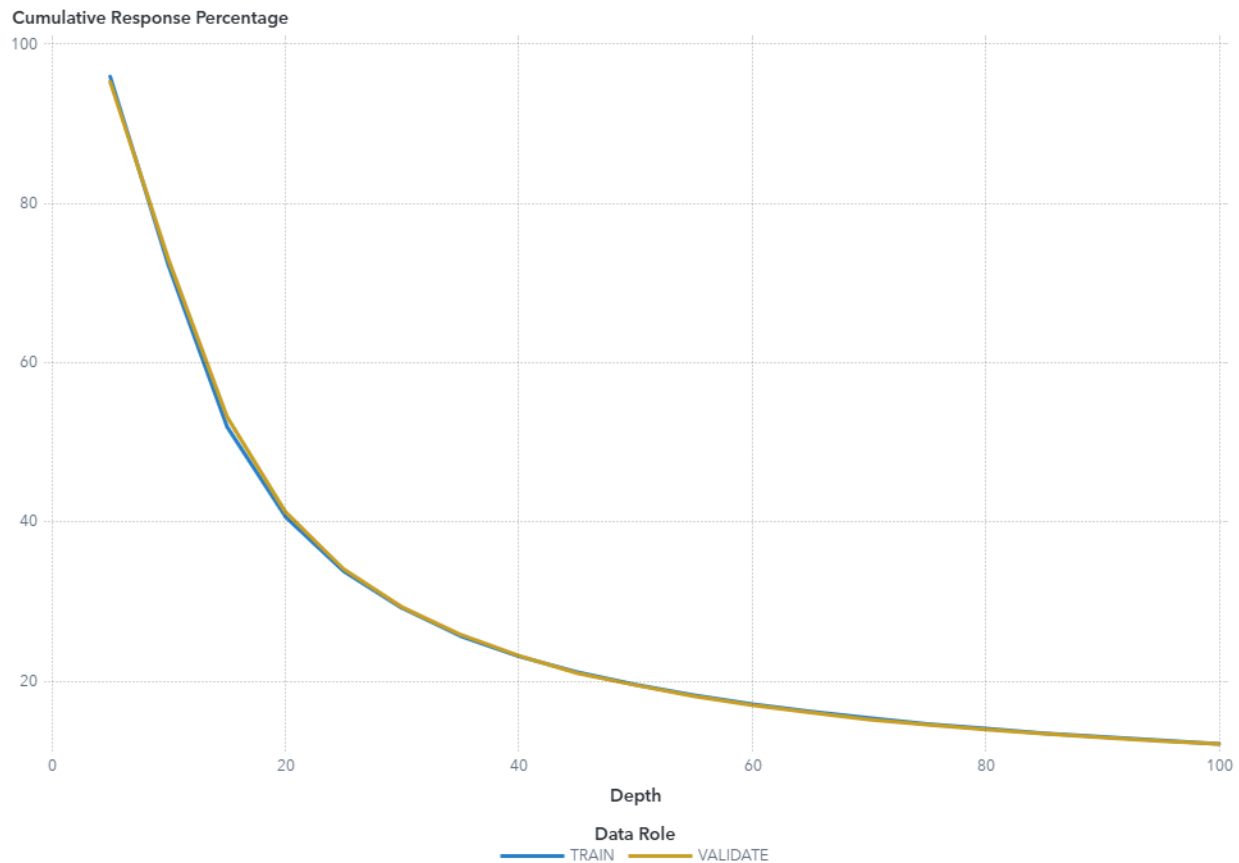


At the 5% quantile (depth of 5), the VALIDATE partition has a Response percentage of 95.3. The best possible value of Response percentage for this partition at depth 5 is 100.

At the 5% quantile (depth of 5), the TRAIN partition has a Response percentage of 96. 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_{churn1} , which represents the predicted probability of the event "1" for the target churn. 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, $100 \times \text{overall-event-rate}$. This is also called the baseline response percentage.

Cumulative Response Percentage

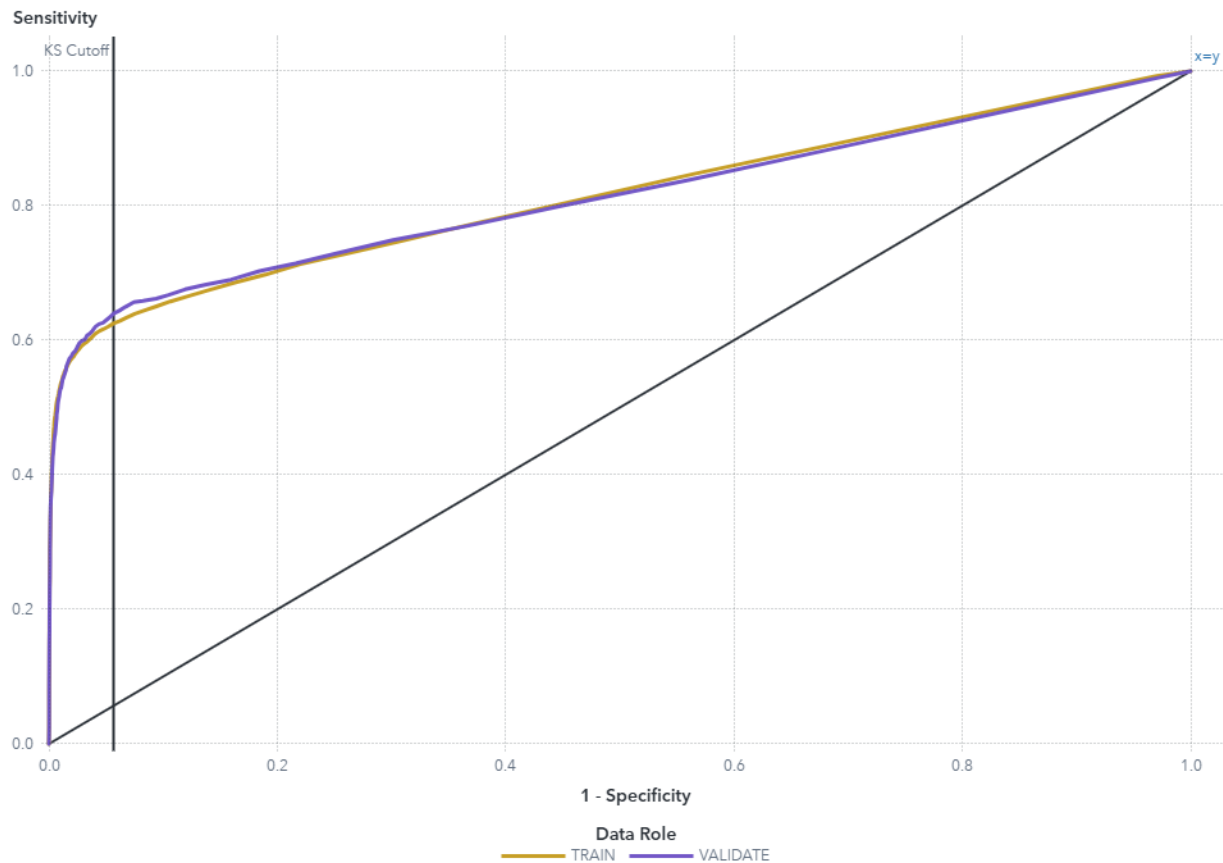


In the top 10% of the data (depth 10), the VALIDATE partition has a Cumulative response percentage of 72.9. The best possible value of Cumulative response percentage for this partition at depth 10 is 100.

In the top 10% of the data (depth 10), the TRAIN partition has a Cumulative response percentage of 72.2. 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_{churn1} , which represents the predicted probability of the event "1" for the target churn. 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, $100 \times \text{overall-event-rate}$. 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 VALIDATE partition. The KS Cutoff line is drawn at the cutoff value 0.2, where the 1-specificity value is 0.057 and the sensitivity value is 0.64.

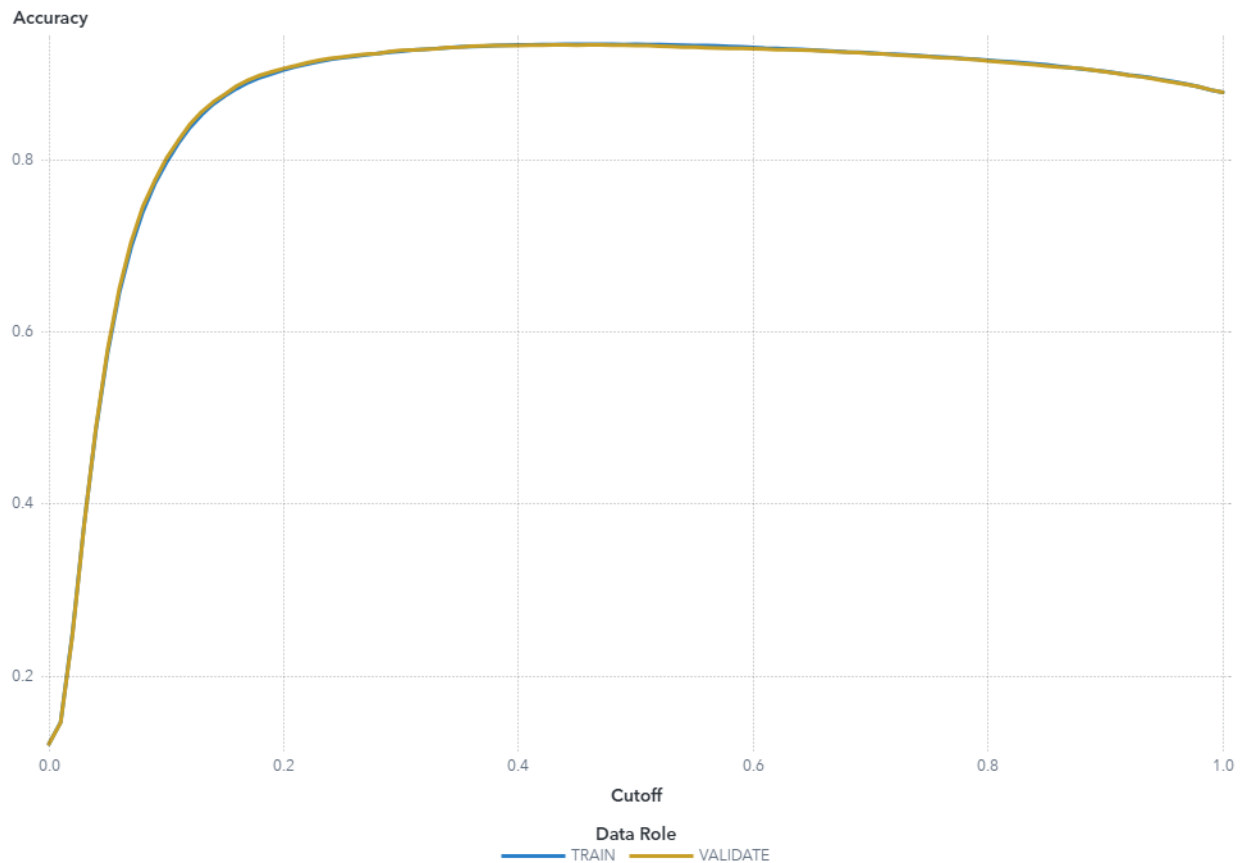
Cutoff values range from 0 to 1, inclusive, in increments of 0.01. At each cutoff value, the predicted target classification is determined by whether P_{churn1} , which is the predicted probability of the event "1" for the target churn, is greater than or equal to the cutoff value. When P_{churn1} is 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

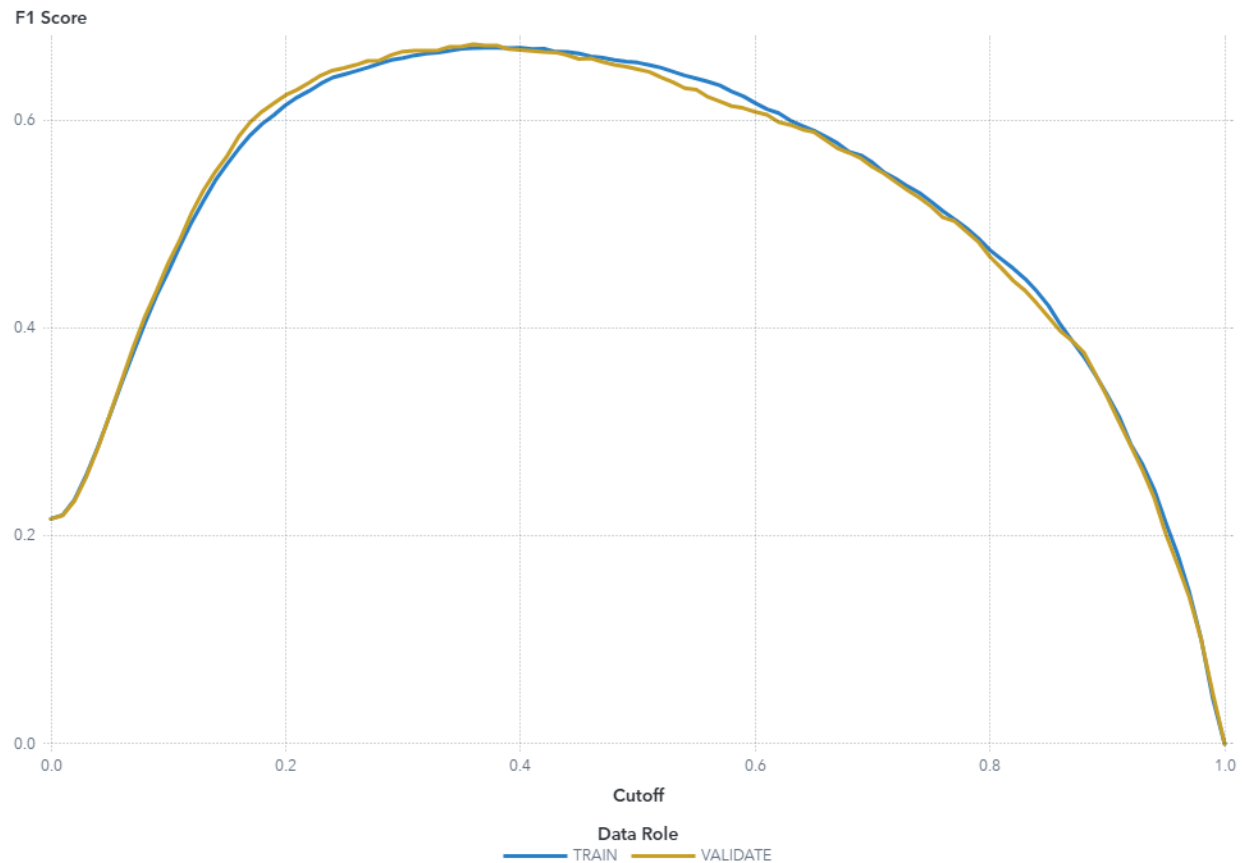


For this model, the accuracy in the TRAIN partition at the cutoff of 0.5 is 0.934.

For this model, the accuracy in the VALIDATE partition at the cutoff of 0.5 is 0.933.

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_{churn1} , which is the predicted probability of the event "1" for the target churn, is greater than or equal to the cutoff value. When P_{churn1} 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 $(\text{true positives} + \text{true negatives}) / (\text{total observations})$.

F1 Score



For this model, the F1 score in the TRAIN partition at the cutoff of 0.5 is 0.655.

For this model, the F1 score in the VALIDATE partition at the cutoff of 0.5 is 0.649.

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_{churn1} , which is the predicted probability of the event "1" for the target churn, is greater than or equal to the cutoff value. When P_{churn1} 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
churn	TRAIN	1	1
churn	VALIDATE	0	0

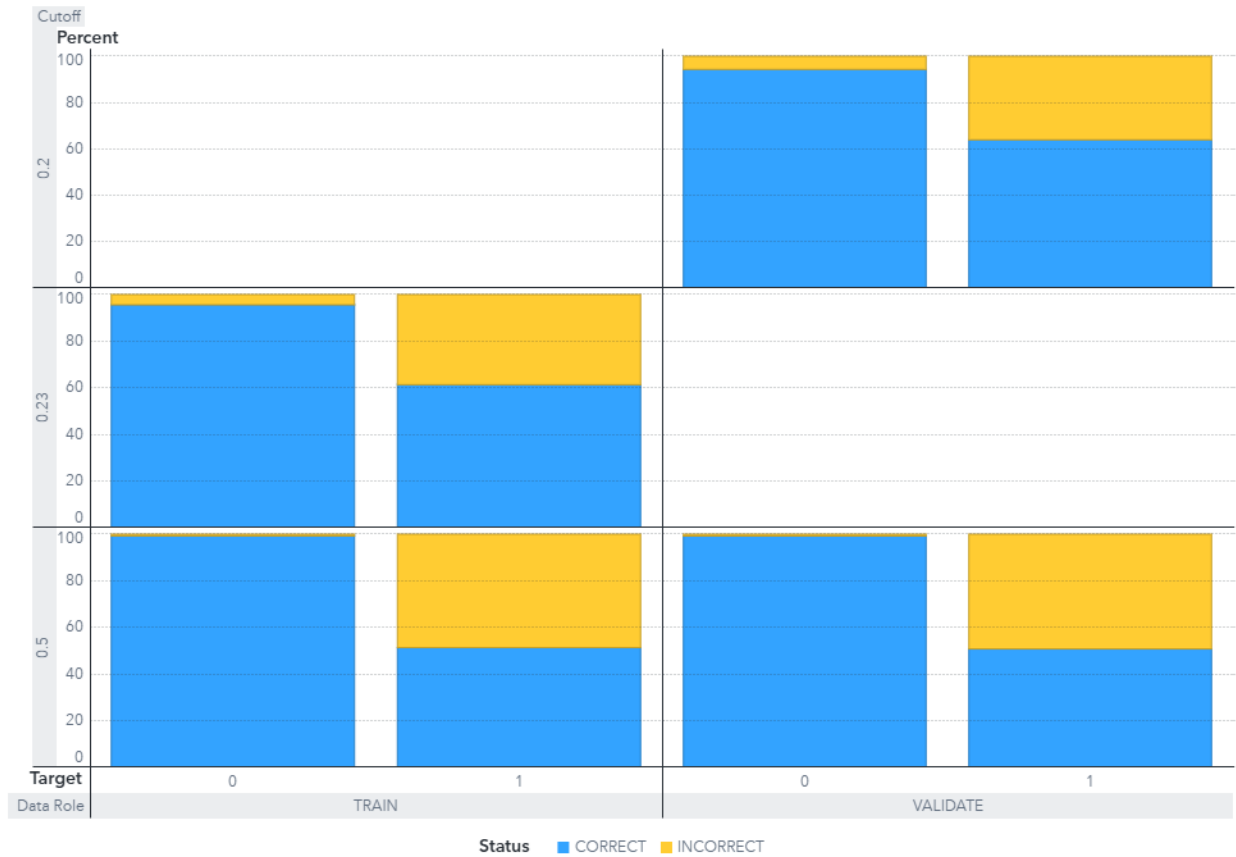
Number of Observations	Average Squared Error	Divisor for ASE	Root Average Squared Error
39,590	0.0599	39,590	0.2448
16,967	0.0598	16,967	0.2446

Misclassification Rate	Multi-Class Log Loss	KS (Youden)	Area Under ROC
0.0656	0.2377	0.5695	0.8137
0.0668	0.2379	0.5829	0.8128

Gini Coefficient	Gamma	Tau	KS Cutoff
0.6274	0.6484	0.1338	0.2300
0.6256	0.6465	0.1334	0.2000

KS at User-Specified Cutoff	Misclassification Rate at KS Cutoff (Event)	Misclassification Rate (Event)
0.5061	0.0856	0.0656
0.5000	0.0936	0.0668

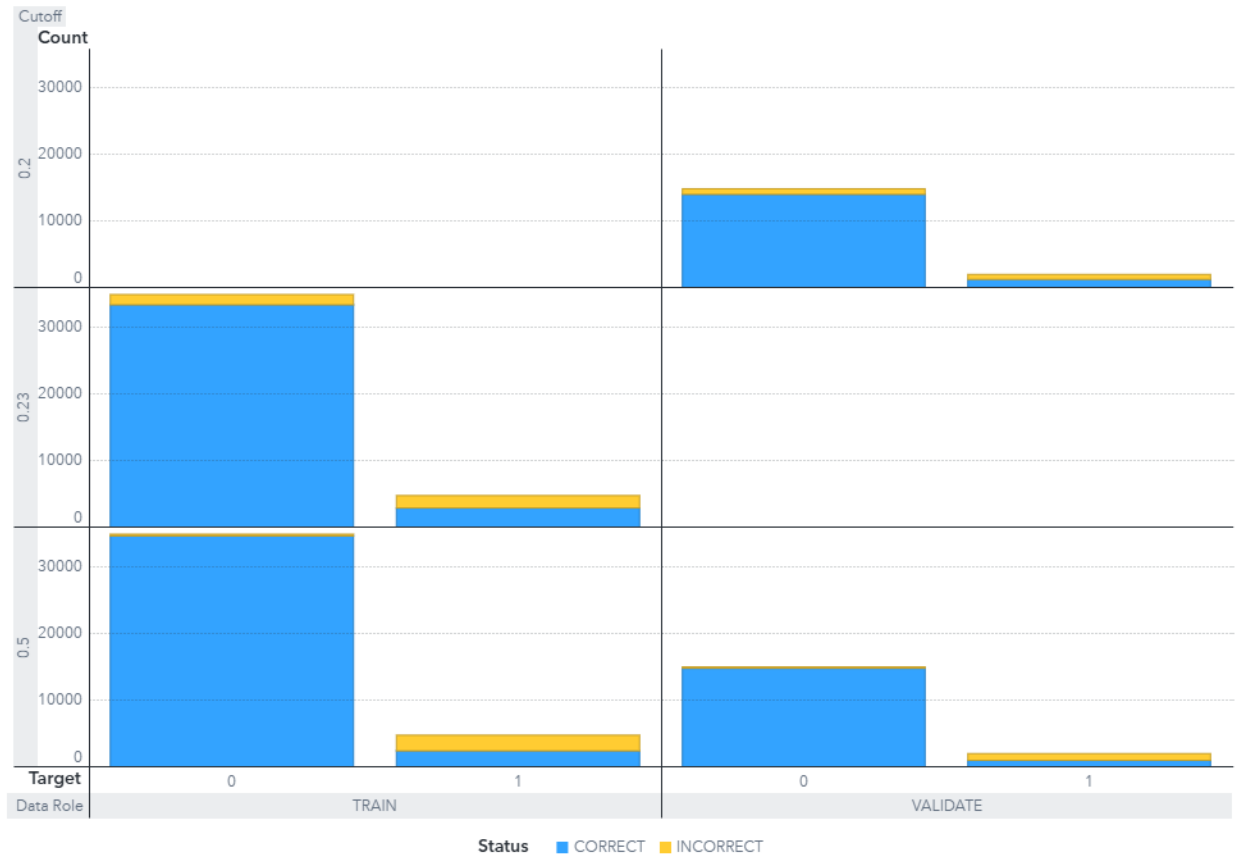
Percentage Plot



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: 0.23 (TRAIN), 0.2 (VALIDATE).

For this data, for the bar corresponding to the event level of churn, "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: 0.23 (TRAIN), 0.2 (VALIDATE).

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

Table

Cutoff	Cutoff Source	Target Name	Response
0.2000	KS	churn	CORRECT
0.2000	KS	churn	INCORRECT
0.2000	KS	churn	CORRECT
0.2000	KS	churn	INCORRECT
0.2300	KS	churn	CORRECT
0.2300	KS	churn	INCORRECT
0.2300	KS	churn	CORRECT
0.2300	KS	churn	INCORRECT
0.5000	Default	churn	CORRECT
0.5000	Default	churn	INCORRECT
0.5000	Default	churn	CORRECT
0.5000	Default	churn	INCORRECT

Event	Value	Training Frequency	Validation Frequency
1	True Positive		1,317
1	False Negative		742
0	True Negative		14,062
0	False Positive		846
1	True Positive	2,947	
1	False Negative	1,856	
0	True Negative	33,254	
0	False Positive	1,533	
1	True Positive	2,467	1,046
1	False Negative	2,336	1,013
0	True Negative	34,525	14,788
0	False Positive	262	120

Test Frequency	Training Percentage	Validation Percentage	Test Percentage
		63.9631	
		36.0369	
		94.3252	
		5.6748	
	61.3575		
	38.6425		
	95.5932		
	4.4068		
	51.3637	50.8014	
	48.6363	49.1986	
	99.2468	99.1951	
	0.7532	0.8049	

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
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
truncateLI	5
truncateUI	95
usePolynomial	false
useSpline	false
useSplineSplit	false
userProbCutoff	false

