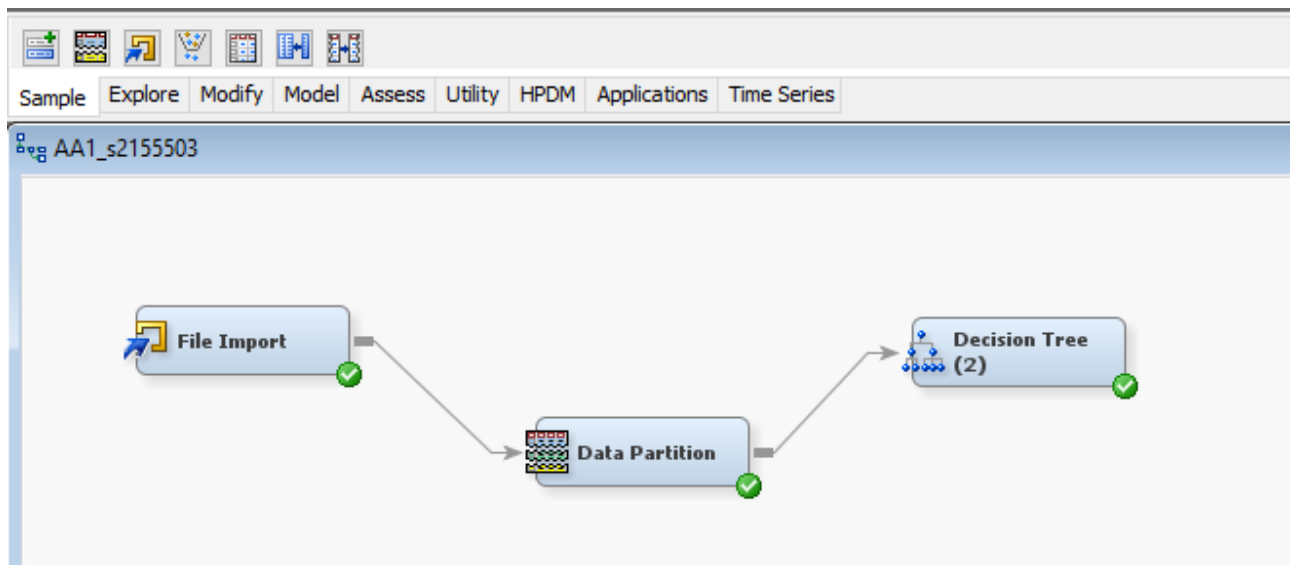


RESULTS AND ANALYSIS

1.0 Tasks 2

Decision Tree Analysis: Create a decision tree model in SAS Enterprise Miner to analyse customer behaviour.



As shown in the diagram, establish a decision tree model by linking three components which are file import, data partitioning, and the decision tree. The specific purpose of the component and property configuration data partitioning and Decision Tree will be discussed in the next section.

Data Partitioning

Property	Value
Exported Data	
Notes	
Train	
Variables	
Output Type	Data
Partitioning Method	Default
Random Seed	12345
Data Set Allocations	
Training	70.0
Validation	30.0
Test	0.0
Report	
Interval Targets	Yes
Class Targets	Yes
Status	
Create Time	1/6/24 11:33 PM
Run ID	7db4e363-e3c5-40de-8e82-0
Last Error	
Last Status	Complete
Last Run Time	1/7/24 12:57 AM
Run Duration	0 Hr. 0 Min. 15.37 Sec.
Grid Host	
User-Added Node	No

Training: 70
 Validation: 30

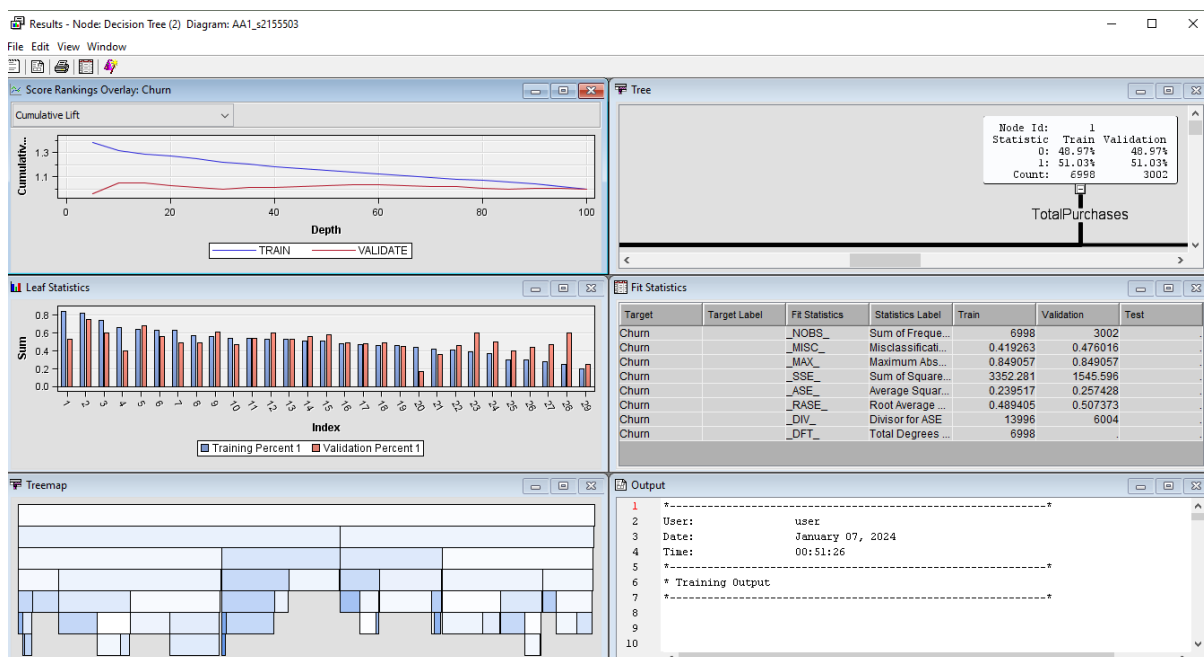
In SAS Enterprise Miner, data partitioning is used to split a dataset into separate subsets for model building and validation, allowing for unbiased assessment of model performance. For this model, I use a 70% portion for training and a 30% portion for validation.

Decision Tree

Property	Value
Variables	
Interactive	
Import Tree Model	No
Tree Model Data Set	
Use Frozen Tree	No
Use Multiple Targets	No
Splitting Rule	
Interval Target Criterion	Variance
Nominal Target Criterion	Entropy
Ordinal Target Criterion	Entropy
Significance Level	0.2
Missing Values	Use in search
Use Input Once	No
Maximum Branch	2
Maximum Depth	6
Minimum Categorical Size	5
Node	
Leaf Size	5
Number of Rules	5
Number of Surrogate Rules	0
Split Size	.
Split Search	
Use Decisions	No

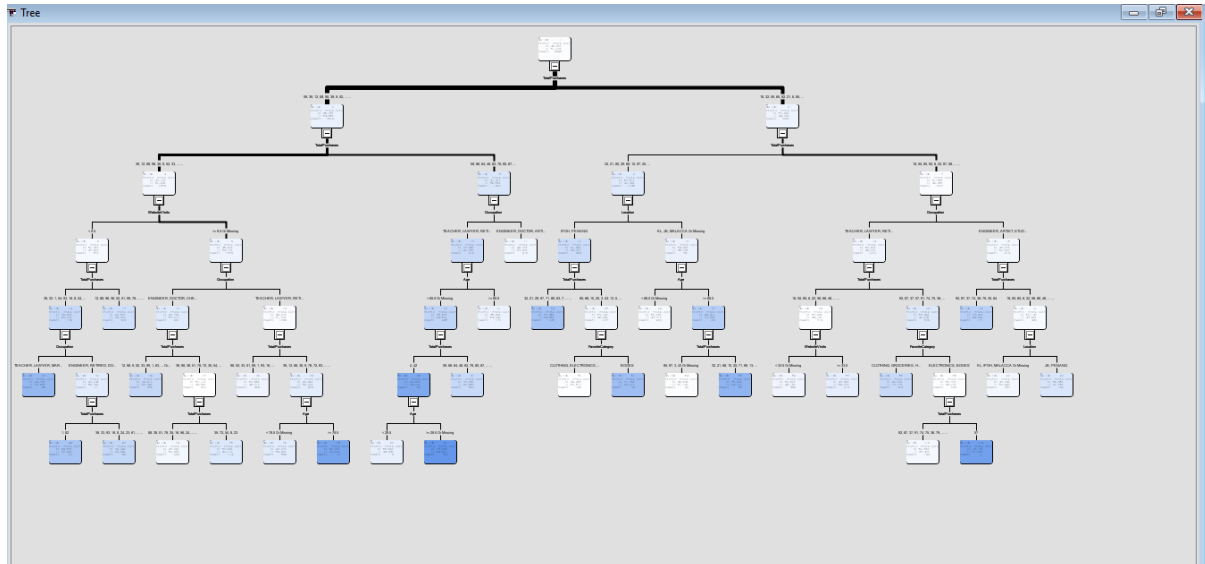
Change the Splitting Rule
 Interval Target Criterion: Variance
 Nominal Target Criterion: Entropy
 Ordinal Target Criterion: Entropy

When building a decision tree model, the splitting rule based on the nature of our target variable. For interval target variables, the criterion often used is Variance, which minimizes the variance within each split. In cases with nominal target variables, the criterion of choice is typically Entropy, which measures the disorder or impurity of data at each split. Similarly, for ordinal target variables, the Entropy criterion is also favoured. By adapting the splitting rule to your specific target variable, you can optimize the performance and interpretability of your decision tree model.



The figure provides an overall result generated by this model. It encompasses various visual elements, including a score ranking overlay, a tree diagram, fit statistics, a treemap, and more.

Here's the complete tree diagram for the model predicting observed target values as shown in below: -

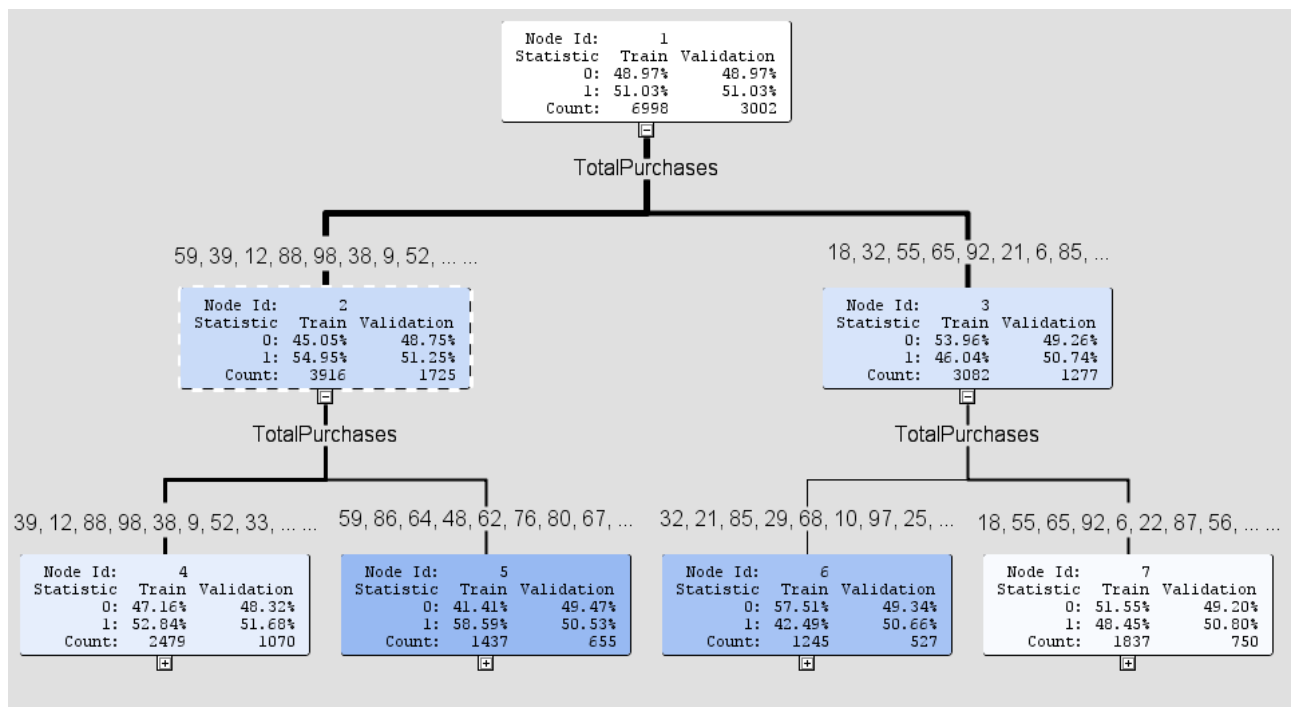


Tree diagram with 14 splitting rules for the input column "TotalPurchases".

Variable Importance

Variable Name	Label	Number of Splitting Rules	Importance	Validation Importance	Ratio of Validation to Training Importance
TotalPurchases		14	1.0000	1.0000	1.0000
Occupation		4	0.3809	0.4956	1.3014
Age		4	0.3516	0.6659	1.8936
FavoriteCategory		2	0.2623	0.0000	0.0000
WebsiteVisits		2	0.2532	0.4962	1.9596
Location		2	0.2510	0.5514	2.1966

According to the Variable Importance table the most important predictors is TotalPurchases.



The decision tree analysis, focusing on 'TotalPurchases', reveals distinct customer segments based on their purchasing behavior. Initial splits in the tree indicate that the number of purchases is a significant predictor of the behavior under study, likely customer churn. The detailed node statistics suggest that as the total number of purchases varies, so does the likelihood of a customer falling into one of two categories, which could signify churned versus active customers.

The further Nodes 4 to 7 suggests more nuanced thresholds of purchase behavior that are influential in predicting outcomes. For instance, certain nodes with higher purchase counts may correlate with a greater likelihood of customer retention, while others with fewer purchases might indicate a risk of churning.

Overall, the decision tree provides actionable insights, suggesting that the frequency of purchases is a key behavioral indicator. This information can be leveraged to tailor customer engagement strategies, such as targeted marketing to increase purchase frequency among customers showing signs of potential churn.

Fit Statistics					
Target	Target Label	Fit Statistics	Statistics Label	Train	Validation
Churn		_NOBS_	Sum of Frequencies	6998	3002
Churn		_MISC_	Misclassification Rate	0.419263	0.476016
Churn		_MAX_	Maximum Absolute Error	0.849057	0.849057
Churn		_SSE_	Sum of Squared Errors	3352.281	1545.596
Churn		_ASE_	Average Squared Error	0.239517	0.257428
Churn		_RASE_	Root Average Squared Error	0.489405	0.507373
Churn		_DIV_	Divisor for ASE	13996	6004
Churn		_DFT_	Total Degrees of Freedom	6998	.

From this Fit Statistics Table, it seems that the misclassification rates maximum error are in acceptable range. The ASE and RASE also suggest that the model's predictions are close to the actual values on average.

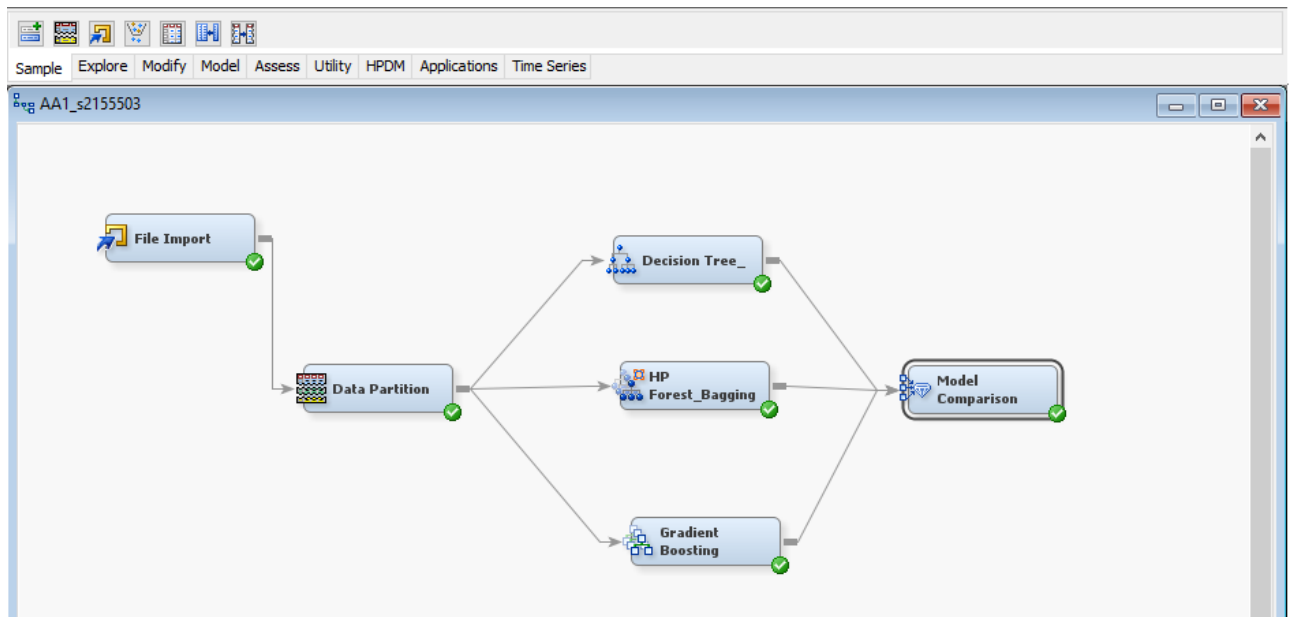
The customer behavior analysis, using decision tree modeling, indicates that the frequency of purchases ('Total Purchases') is the most critical factor in determining customer churn, with other variables such as 'Occupation' and 'Age' also playing significant roles. 'Total Purchases' is the principal variable used to split decisions in the predictive tree, suggesting thresholds in purchasing behavior are key indicators of churn risk. The variable importance scores reveal 'Age' as a more significant predictor in the validation set than in training, suggesting demographic factors may influence churn differently across datasets.

The fit statistics exhibit a moderate misclassification rate, with the model being more accurate on training data compared to validation data, hinting at potential overfitting. The Average Squared Error (ASE) and Root Average Squared Error (RASE) point to a moderate error level in predictions, with these errors slightly inflated in the validation set, indicating room for improvement in the model's predictive accuracy.

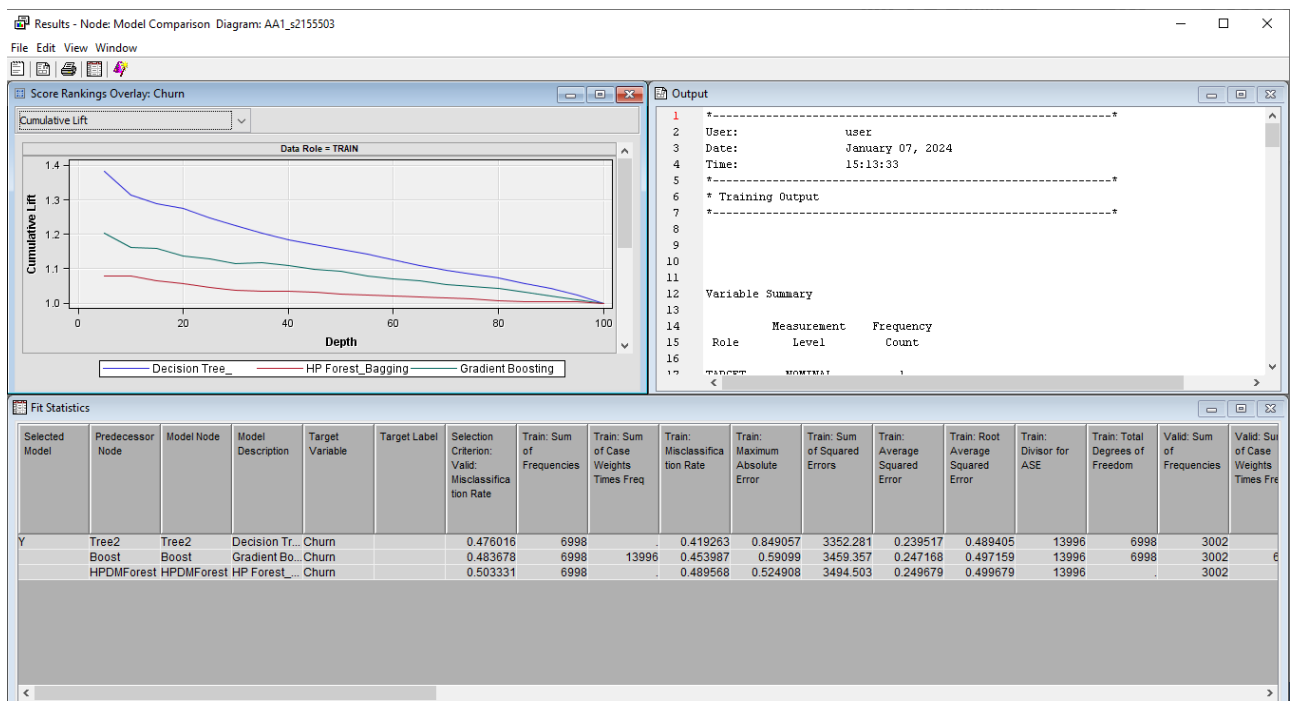
Overall, the analysis underscores the need to consider how various factors like purchasing frequency, occupation, and age interplay in influencing customer retention. There is also a suggestion of the need to address overfitting and enhance the model's generalization capabilities to better predict churn across different customer segments.

2.0 Tasks 3

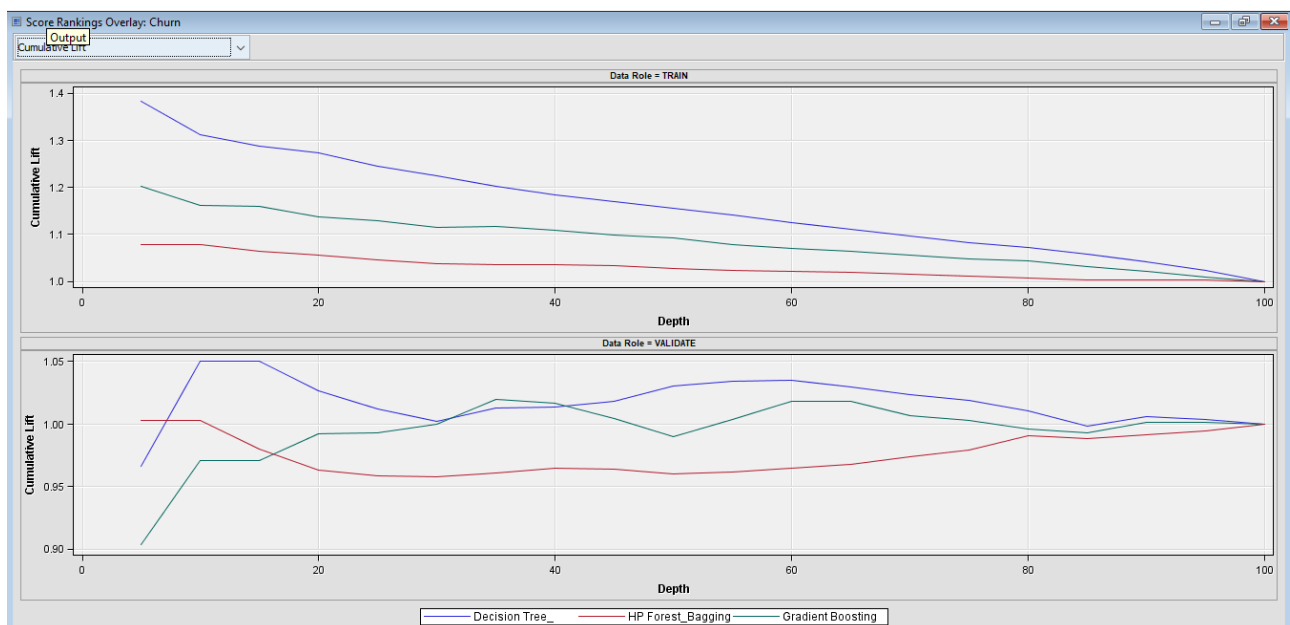
Ensemble Methods: Apply Bagging and Boosting, using the Random Forest algorithm as a Bagging example.



In this SAS Enterprise Miner workflow, I've constructed an ensemble methods approach to enhance predictive performance, building upon the foundation laid by the decision tree model established in the earlier task. The ensemble methodology is incorporating two components which are the HP Forest and Gradient Boosting. The HP Forest is for the bagging technique using the Random Forest algorithm, which aggregates multiple decision trees to reduce variance and improve stability. On the other hand, the Gradient Boosting component implements boosting, a method that sequentially builds models with each one focusing on the errors of the previous model to reduce bias. To systematically assess the efficacy of these models, the Model Comparison component is employed to leverages the collective strengths of bagging and boosting to potentially outperform the individual predictive capabilities of the models involved.



The figure provides an overall result generated by the model comparison component. It encompasses of a score ranking overlay, fit statistics, and output file.



The chart displays the performance of three models which are Decision Tree, HP Forest (Bagging), and Gradient Boosting across different complexities, as indicated by depth. For the training data, Gradient Boosting consistently outperforms the other models, maintaining a higher cumulative lift across all depths. In contrast, the Decision Tree and HP Forest show a decreasing lift with increasing depth. On the validation set, the Decision Tree's performance drops as complexity grows, while the HP Forest and Gradient Boosting display more stable trends. Overall, Gradient Boosting seems to offer the best performance, particularly at higher depths, indicating its effectiveness in both training and validation scenarios.

Fit Statistics

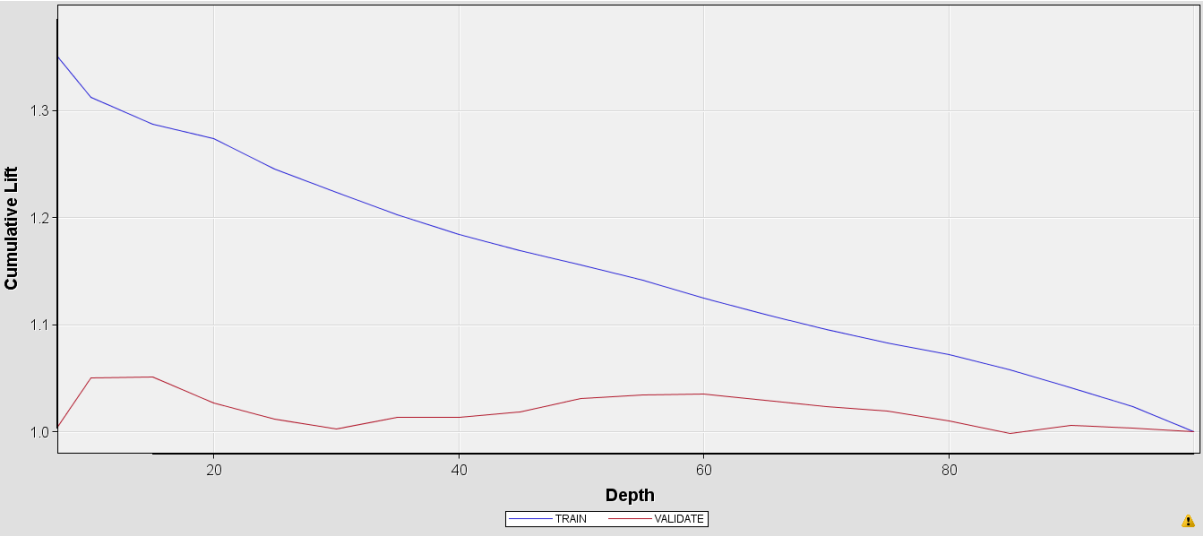
Model Selection based on Valid: Misclassification Rate (_VMISC_)

Selected Model	Model Node	Model Description	Valid:	Train:	Train:	Valid:
			Misclassification Rate	Average Squared Error	Misclassification Rate	Average Squared Error
Y	Tree2	Decision Tree (2)	0.47602	0.23952	0.41926	0.25743
	Boost	Gradient Boosting	0.48368	0.24717	0.45399	0.25129
	HPDMForest	HP Forest	0.50333	0.24968	0.48957	0.25033

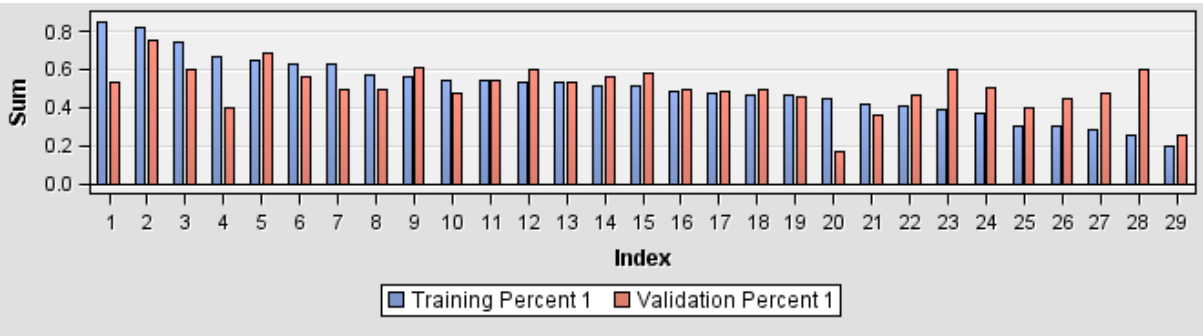
For the training set, the Decision Tree model has a misclassification rate of 0.41926 and an average squared error of 0.23952. The Gradient Boosting model shows a similar misclassification rate of 0.45399 but has a slightly better average squared error of 0.2417. The HP Forest model presents the highest misclassification rate among the three at 0.48957 with an average squared error of 0.24968. These statistics suggest that while the Decision Tree and Gradient Boosting models have a closer performance in terms of error, the HP Forest model is less accurate on the training data.

Appendix

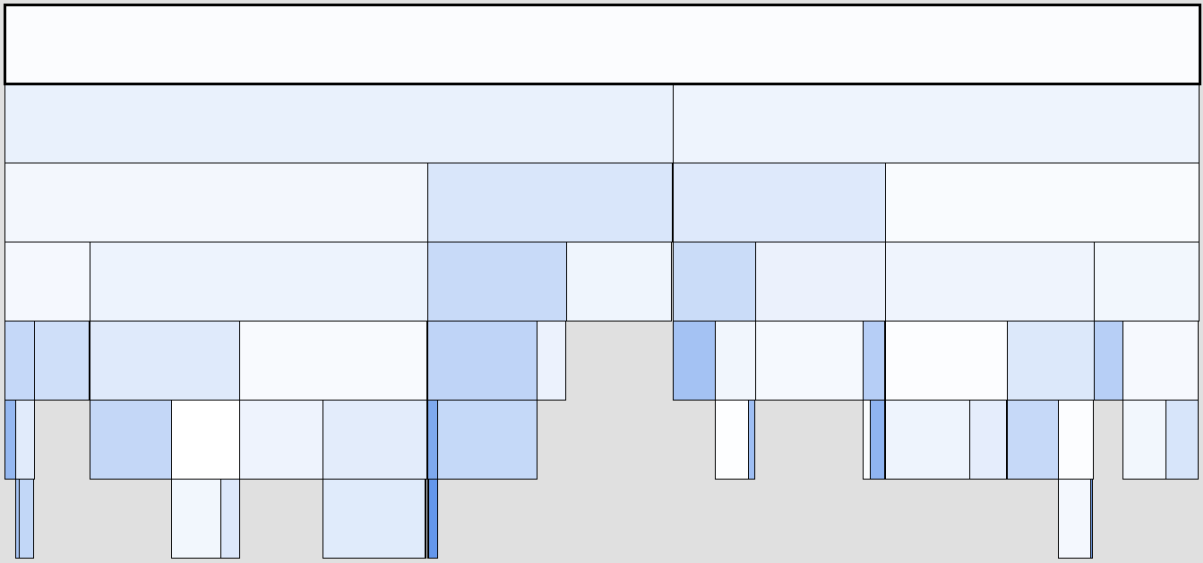
Score Rankings Overlays: Churn



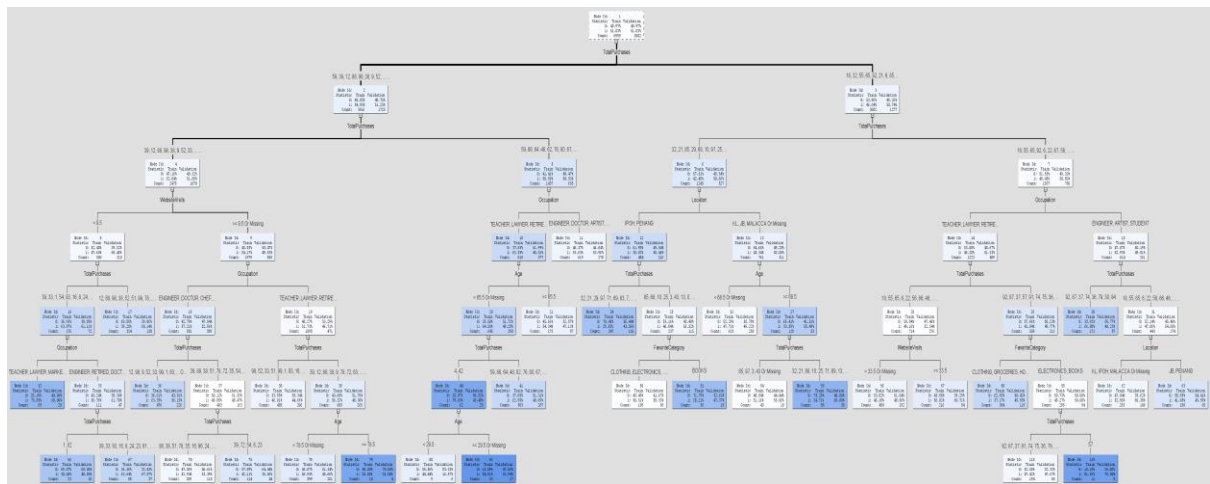
Leaf Statistics



TreeMap



Tree



Fit Statistics

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test
Churn		_NOBS_	Sum of Frequencies	6998	3002	
Churn		_MISC_	Misclassification Rate	0.419263	0.476016	
Churn		_MAX_	Maximum Absolute Error	0.849057	0.849057	
Churn		_SSE_	Sum of Squared Errors	3352.281	1545.596	
Churn		_ASE_	Average Squared Error	0.239517	0.257428	
Churn		_RASE_	Root Average Squared Error	0.489405	0.507373	
Churn		_DIV_	Divisor for ASE	13996	6004	
Churn		_DFT_	Total Degrees of Freedom	6998		

User: user

Date: January 07, 2024

Time: 00:57:51

* Training Output

Variable Summary

Role	Measurement Level	Frequency Count
ID	INTERVAL	1
ID	NOMINAL	1
INPUT	INTERVAL	2
INPUT	NOMINAL	6
INPUT	ORDINAL	1
TARGET	NOMINAL	1
TIMEID	INTERVAL	1

Model Events

		Number Measurement of Level Levels	Order	Label
Churn	1	NOMINAL	2	Descending

Predicted and decision variables

Type	Variable	Label
------	----------	-------

TARGET	Churn	
PREDICTED	P_Churn1	Predicted: Churn=1
RESIDUAL	R_Churn1	Residual: Churn=1
PREDICTED	P_Churn0	Predicted: Churn=0
RESIDUAL	R_Churn0	Residual: Churn=0
FROM	F_Churn	From: Churn
INTO	I_Churn	Into: Churn

* Score Output

* Report Output

Variable Importance

Variable Name	Number of Splitting Label	Rules	Validation Importance	Ratio of Validation to Training Importance	Importance
TotalPurchases	14		1.0000	1.0000	1.0000
Occupation	4		0.3809	0.4956	1.3014
Age	4		0.3516	0.6659	1.8936
FavoriteCategory	2		0.2623	0.0000	0.0000
WebsiteVisits	2		0.2532	0.4962	1.9596
Location	2		0.2510	0.5514	2.1966

Tree Leaf Report

Node Id	Depth	Training		Validation Observations	Validation Percent 1
		Training Observations	Percent 1		
26	4	633	0.48	258	0.49
11	3	619	0.54	278	0.54
78	6	599	0.57	261	0.49
41	5	583	0.63	267	0.49
56	5	498	0.46	192	0.49
38	5	489	0.46	206	0.45
36	5	478	0.63	226	0.56
17	4	324	0.39	138	0.60
58	5	304	0.37	119	0.50
74	6	289	0.53	118	0.53
62	5	253	0.53	106	0.60
24	4	247	0.30	101	0.44
57	5	216	0.56	84	0.61
50	5	198	0.51	96	0.58
118	6	194	0.47	86	0.48
63	5	190	0.41	68	0.46
21	4	173	0.54	87	0.47
30	4	171	0.66	87	0.40
75	6	114	0.42	45	0.36
67	6	88	0.64	37	0.68
55	5	85	0.25	35	0.60
32	5	65	0.74	25	0.60
81	6	53	0.85	17	0.53
54	5	43	0.51	18	0.56
51	5	39	0.28	19	0.47
66	6	23	0.30	10	0.40
119	6	11	0.82	8	0.75
79	6	10	0.20	4	0.25
80	6	9	0.44	6	0.17

Fit Statistics

Target=Churn Target Label=' '

Fit		Train	Validation
Statistics	Statistics Label		
NOBS	Sum of Frequencies	6998.00	3002.00
MISC	Misclassification Rate	0.42	0.48
MAX	Maximum Absolute Error	0.85	0.85
SSE	Sum of Squared Errors	3352.28	1545.60
ASE	Average Squared Error	0.24	0.26
RASE	Root Average Squared Error	0.49	0.51

DIV	Divisor for ASE	13996.00	6004.00
DFT	Total Degrees of Freedom	6998.00	.

Classification Table

Data Role=TRAIN Target Variable=Churn Target Label=' '

	Target	Outcome	Frequency	Total	
Target	Outcome	Percentage	Percentage	Count	Percentage
0	0	57.8031	53.2828	1826	26.0932
1	0	42.1969	37.3285	1333	19.0483
0	1	41.7036	46.7172	1601	22.8780
1	1	58.2964	62.6715	2238	31.9806

Data Role=VALIDATE Target Variable=Churn Target Label=' '

	Target	Outcome	Frequency	Total	
Target	Outcome	Percentage	Percentage	Count	Percentage
0	0	51.5929	45.1701	664	22.1186
1	0	48.4071	40.6658	623	20.7528
0	1	46.9971	54.8299	806	26.8488
1	1	53.0029	59.3342	909	30.2798

Event Classification Table

Data Role=TRAIN Target=Churn Target Label=' '

False	True	False	True
Negative	Negative	Positive	Positive
1333	1826	1601	2238

Data Role=VALIDATE Target=Churn Target Label=' '

False	True	False	True
Negative	Negative	Positive	Positive
623	664	806	909

Assessment Score Rankings

Data Role=TRAIN Target Variable=Churn Target Label=' '

Depth	Gain	Mean		% Response	Cumulative % Response	Number of Observations	Posterior Probability
		Cumulative Lift	% Lift				
5	38.1953	1.38195	1.38195	70.5195	70.5195	350	0.70519
10	31.2350	1.24275	1.31235	63.4160	66.9677	350	0.63416
15	28.7466	1.23770	1.28747	63.1584	65.6979	350	0.63158
20	27.4005	1.23362	1.27400	62.9503	65.0110	350	0.62950
25	24.5630	1.13213	1.24563	57.7713	63.5631	350	0.57771
30	22.3518	1.11296	1.22352	56.7931	62.4347	350	0.56793
35	20.2979	1.07974	1.20298	55.0980	61.3866	350	0.55098
40	18.3990	1.05107	1.18399	53.6349	60.4177	350	0.53635
45	16.8829	1.04754	1.16883	53.4548	59.6440	350	0.53455
50	15.5748	1.03768	1.15575	52.9518	58.9765	349	0.52952
55	14.1882	1.00326	1.14188	51.1951	58.2689	350	0.51195
60	12.4633	0.93495	1.12463	47.7093	57.3887	350	0.47709
65	10.9944	0.93371	1.10994	47.6463	56.6392	350	0.47646
70	9.5886	0.91318	1.09589	46.5986	55.9218	350	0.46599
75	8.3108	0.90425	1.08311	46.1429	55.2698	350	0.46143
80	7.1767	0.90169	1.07177	46.0123	54.6911	350	0.46012
85	5.7421	0.82792	1.05742	42.2479	53.9590	350	0.42248
90	4.1389	0.76889	1.04139	39.2355	53.1409	350	0.39236
95	2.3740	0.70611	1.02374	36.0320	52.2403	350	0.36032
100	0.0000	0.54771	1.00000	27.9491	51.0289	349	0.27949

Data Role=VALIDATE Target Variable=Churn Target Label=' '

Depth	Gain	Mean		% Response	Cumulative % Response	Number of Observations	Posterior Probability
		Cumulative Lift	% Lift				
5	3.37381	0.96626	0.96626	49.3109	49.3109	151	0.70094
10	5.05116	1.13532	1.05051	57.9385	53.6104	150	0.63427
15	5.07229	1.05115	1.05072	53.6428	53.6212	150	0.63240
20	2.66019	0.95408	1.02660	48.6891	52.3902	150	0.62950
25	1.20505	0.95375	1.01205	48.6723	51.6476	150	0.59578
30	0.23008	0.95349	1.00230	48.6590	51.1501	150	0.56928
35	1.31000	1.07797	1.01310	55.0115	51.7012	150	0.55745
40	1.32711	1.01447	1.01327	51.7711	51.7099	150	0.53859
45	1.81597	1.05730	1.01816	53.9568	51.9594	150	0.53635
50	3.08227	1.14487	1.03082	58.4260	52.6056	150	0.53078
55	3.46247	1.07242	1.03462	54.7284	52.7996	151	0.52197
60	3.50337	1.03954	1.03503	53.0504	52.8205	150	0.48884
65	2.96194	0.96457	1.02962	49.2248	52.5442	150	0.47709
70	2.36280	0.94566	1.02363	48.2595	52.2384	150	0.47108

75	1.93094	0.95879	1.01931	48.9297	52.0181	150	0.46184
80	1.03057	0.87513	1.01031	44.6602	51.5586	150	0.46012
85	0.17616	0.80500	0.99824	41.0813	50.9427	150	0.43323
90	0.57151	1.13292	1.00572	57.8159	51.3243	150	0.39494
95	0.37581	0.96851	1.00376	49.4255	51.2244	150	0.36427
100	0.00000	0.92855	1.00000	47.3861	51.0326	150	0.27998

Assessment Score Distribution

Data Role=TRAIN Target Variable=Churn Target Label=' '

Posterior Probability Range	Number of Events	Number of Nonevents	Mean Posterior Probability	Percentage
0.80-0.85	54	10	0.84375	0.9145
0.70-0.75	48	17	0.73846	0.9288
0.65-0.70	113	58	0.66082	2.4436
0.60-0.65	726	423	0.63185	16.4190
0.55-0.60	462	353	0.56687	11.6462
0.50-0.55	835	740	0.53016	22.5064
0.45-0.50	849	965	0.46803	25.9217
0.40-0.45	130	183	0.41534	4.4727
0.35-0.40	240	388	0.38217	8.9740
0.30-0.35	7	16	0.30435	0.3287
0.25-0.30	84	202	0.29371	4.0869
0.20-0.25	21	64	0.24706	1.2146
0.15-0.20	2	8	0.20000	0.1429

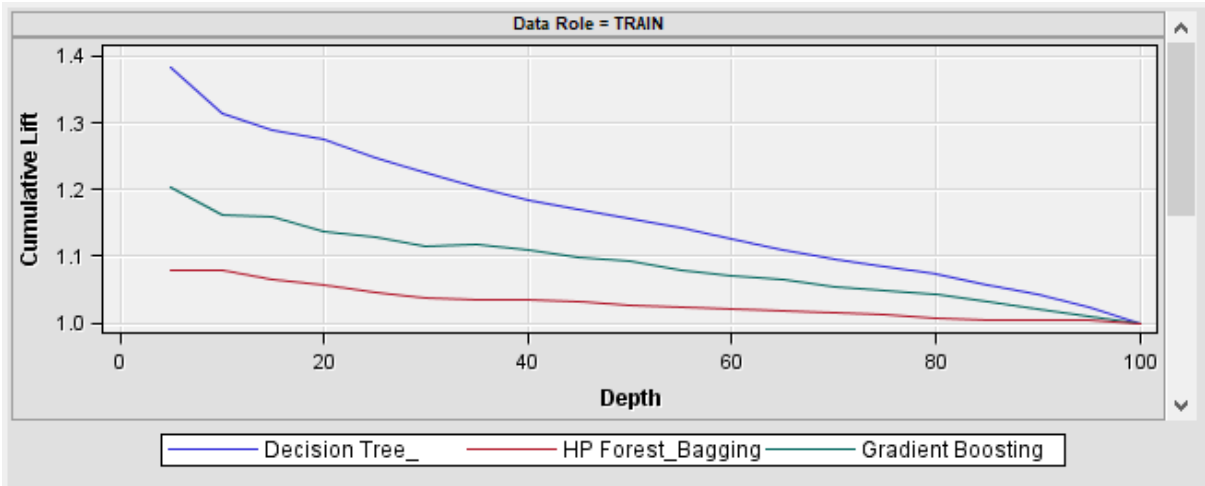
Data Role=VALIDATE Target Variable=Churn Target Label=' '

Posterior Probability Range	Number of Events	Number of Nonevents	Mean Posterior Probability	Percentage
0.80-0.85	15	10	0.83918	0.8328
0.70-0.75	15	10	0.73846	0.8328
0.65-0.70	35	52	0.66082	2.8981
0.60-0.65	282	248	0.63185	17.6549
0.55-0.60	178	167	0.56707	11.4923
0.50-0.55	384	319	0.53013	23.4177
0.45-0.50	354	388	0.46810	24.7169
0.40-0.45	48	71	0.41622	3.9640
0.35-0.40	142	115	0.38259	8.5610
0.30-0.35	4	6	0.30435	0.3331
0.25-0.30	53	67	0.29341	3.9973
0.20-0.25	21	14	0.24706	1.1659

0.15-0.20	1	3	0.20000	0.1332
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TASK 2

Score Ranking Overlays: Churn



Fit Statistics

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Misclassification Rate	Train: Sum of Frequencies	Train: Sum of Case Weights Times Freq	Train: Misclassification Rate	Train: Maximum Absolute Error	Train: Sum of Squared Errors	Train: Average Squared Error	Train: Root Average Squared Error	Train: Divisor for ASE	Train: Total Degrees of Freedom	Valid: Sum of Frequencies
Y	Tree2	Tree2	Decision Tr...	Churn		0.476016	6998		0.419263	0.849057	3352.281	0.239517	0.489405	13996	6998	3002
	Boost	Boost	Gradient Bo...	Churn		0.483678	6998	13996	0.453987	0.59099	3459.357	0.247168	0.497159	13996	6998	3002
	HPDMForest	HPDMForest	HP Forest_...	Churn		0.503331	6998		0.489568	0.524908	3494.503	0.249679	0.499679	13996		3002

User: user

Date: January 07, 2024

Time: 15:13:33

* Training Output

Variable Summary

Role	Measurement Level	Frequency Count
TARGET	NOMINAL	1

Fit Statistics

Model Selection based on Valid: Misclassification Rate (_VMISC_)

Selected Model	Model Node	Model Description	Train:		Valid:	
			Valid:	Average	Train:	Average
			Misclassification Rate	Squared Error	Misclassification Rate	Squared Error
Y	Tree2	Decision Tree (2)	0.47602	0.23952	0.41926	0.25743
	Boost	Gradient Boosting	0.48368	0.24717	0.45399	0.25129
	HPDMForest	HP Forest	0.50333	0.24968	0.48957	0.25033

Fit Statistics Table

Target: Churn

Data Role=Train

Statistics	Tree2	Boost	HPDMForest
Train: Bin-Based Two-Way Kolmogorov-Smirnov Probability Cutoff	0.50	0.51	0.51
Train: Kolmogorov-Smirnov Statistic	0.16	0.10	0.03
Train: Average Squared Error	0.24	0.25	0.25
Train: Roc Index	0.61	0.56	0.52
Train: Cumulative Percent Captured Response	13.13	11.61	10.78
Train: Percent Captured Response	6.22	5.60	5.39
Selection Criterion: Valid: Misclassification Rate	0.48	0.48	0.50
Train: Total Degrees of Freedom	6998.00	6998.00	.
Train: Frequency of Classified Cases	.	.	6998.00
Train: Divisor for ASE	13996.00	13996.00	13996.00
Train: Gain	31.23	16.07	7.77
Train: Gini Coefficient	0.23	0.13	0.04
Train: Bin-Based Two-Way Kolmogorov-Smirnov Statistic	0.16	0.10	0.03
Train: Kolmogorov-Smirnov Probability Cutoff	0.51	0.51	0.51
Train: Cumulative Lift	1.31	1.16	1.08
Train: Lift	1.24	1.12	1.08
Train: Maximum Absolute Error	0.85	0.59	0.52
Train: Misclassification Rate	0.42	0.45	0.49
Train: Sum of Frequencies	6998.00	6998.00	6998.00

Train: Root Average Squared Error	0.49	0.50	0.50
Train: Cumulative Percent Response	66.97	59.23	54.99
Train: Percent Response	63.42	57.09	54.99
Train: Sum of Squared Errors	3352.28	3459.36	3494.50
Train: Sum of Case Weights Times Freq	.	13996.00	.
Train: Number of Wrong Classifications	.	.	3426.00

Data Role=Valid

Statistics	Tree2	Boost	HPDMForest
Valid: Kolmogorov-Smirnov Statistic	0.05	0.03	0.04
Valid: Average Squared Error	0.26	0.25	0.25
Valid: Roc Index	0.52	0.50	0.48
Valid: Bin-Based Two-Way Kolmogorov-Smirnov Probability Cutoff	0.49	0.50	0.53
Valid: Cumulative Percent Captured Response	10.53	9.73	10.06
Valid: Percent Captured Response	5.67	5.19	5.01
Valid: Frequency of Classified Cases	.	.	3002.00
Valid: Divisor for VASE	6004.00	6004.00	6004.00
Valid: Gain	5.05	2.95	0.30
Valid: Gini Coefficient	0.03	0.01	-0.05
Valid: Bin-Based Two-Way Kolmogorov-Smirnov Statistic	0.04	0.02	0.00
Valid: Kolmogorov-Smirnov Probability Cutoff	0.48	0.50	0.51
Valid: Cumulative Lift	1.05	0.97	1.00
Valid: Lift	1.14	1.04	1.00
Valid: Maximum Absolute Error	0.85	0.59	0.52
Valid: Misclassification Rate	0.48	0.48	0.50
Valid: Sum of Frequencies	3002.00	3002.00	3002.00
Valid: Root Average Squared Error	0.51	0.50	0.50
Valid: Cumulative Percent Response	53.61	49.53	51.18
Valid: Percent Response	57.94	52.98	51.18
Valid: Sum of Squared Errors	1545.60	1508.76	1503.00
Valid: Sum of Case Weights Times Freq	.	6004.00	.
Valid: Number of Wrong Classifications	.	.	1511.00

Event Classification Table

Model Selection based on Valid: Misclassification Rate (_VMISC_)

Data	Target	False	True	False	True			
Model Node	Model Description	Role	Target	Label	Negative	Negative	Positive	Positive

Boost	Gradient Boosting	TRAIN	Churn	1176	1426	2001	2395
Boost	Gradient Boosting	VALIDATE	Churn	535	553	917	997
Tree2	Decision Tree (2)	TRAIN	Churn	1333	1826	1601	2238
Tree2	Decision Tree (2)	VALIDATE	Churn	623	664	806	909
HPDMForest	HP Forest	TRAIN	Churn	510	511	2916	3061
HPDMForest	HP Forest	VALIDATE	Churn	258	217	1253	1274

* Score Output

* Report Output
