Dataset Description

The dataset is from Kaggle, containing information about customers of an e-commerce company. There are 20 columns of data in total. The following summarizes the variable names and descriptions in the dataset.

CustomerID (Categorical - Nominal): Unique identifier assigned to each customer. This variable serves as an identifier and is not used for analytical purposes other than uniquely identifying customers.

Churn (Categorical - Binary): Indicates whether the customer has churned or not. It's a binary categorical variable with values TRUE (churned) or FALSE (not churned).

Tenure (Numerical - Interval): Represents the duration of the customer's association with the business. It is a quantitative and continuous variable, indicating the length of the customer's tenure.

PreferredLoginDevice (Categorical - Nominal): Represents the preferred device for customer login. This is a categorical variable with different device categories.

CityTier (Categorical - Ordinal): Indicates the tier of the city where the customer is located. It's an ordinal categorical variable with different city tier levels.

WarehouseToHome (Numerical - Interval): Represents the distance from the warehouse to the customer's home. It is a quantitative and continuous variable.

PreferredPaymentMode (Categorical - Nominal): Specifies the preferred mode of payment chosen by the customer. It's a categorical variable with different payment mode categories.

Gender (Categorical - Nominal): Represents the gender of the customer. It's a categorical variable with two possible values: Male or Female.

HourSpendOnApp (Numerical - Interval): Indicates the number of hours the customer spends on the mobile application. This variable is quantitative and continuous.

NumberOfDeviceRegistered (Numerical - Interval): Represents the number of devices registered by the customer. It is a quantitative and discrete variable.

PreferedOrderCat (Categorical - Nominal): Indicates the preferred category for ordering. This is a categorical variable with different order category options.

SatisfactionScore (Numerical - Interval): Reflects the satisfaction score given by the customer. This variable is quantitative and continuous.

MaritalStatus (Categorical - Nominal): Represents the marital status of the customer. It's a categorical variable with values like Single, Married, etc.

NumberOfAddress (Numerical - Interval): Indicates the number of addresses associated with the customer. It is a quantitative and discrete variable.

Complain (Categorical - Binary): Indicates whether the customer has lodged a complaint. It's a binary categorical variable with values TRUE or FALSE.

OrderAmountHikeFromlastYear (Numerical - Interval): Represents the percentage increase in order amount from the last year. This variable is quantitative and continuous.

CouponUsed (Numerical - Interval): Indicates the number of coupons used by the customer. It is a quantitative and discrete variable.

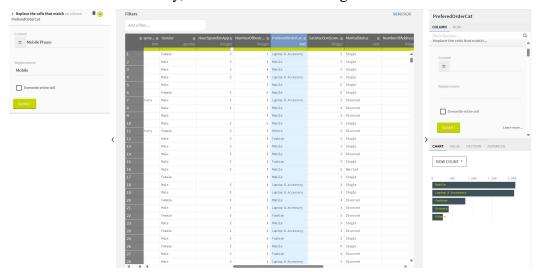
OrderCount (Numerical - Interval): Represents the count of orders placed by the customer. It is a quantitative and discrete variable.

DaySinceLastOrder (Numerical - Interval): Represents the number of days since the customer's last order. It is a quantitative and continuous variable.

CashbackAmount (Numerical - Interval): Reflects the cashback amount received by the customer. This variable is quantitative and continuous.

1.Data Pre-processing using Talend Data Preparation

In the "PreferredOrderCat" column, "Mobile Phone" should be a subset of "Mobile". To ensure data consistency, "Mobile Phone" is changed to "Mobile".



In the "WarehouseToHome" column, there are many missing values. Use Delete the rows with empty cell to delete the missing values.

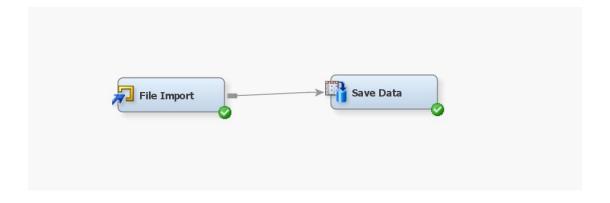


Similarly, missing values in other columns were deleted, and a total of 1856 rows of data containing missing values were deleted.

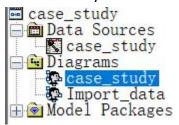


2.Data import using SAS Enterprise Miner

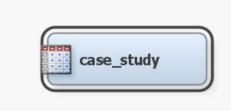
1. Import the CSV file using "File Import" node. Save it as a SAS file.



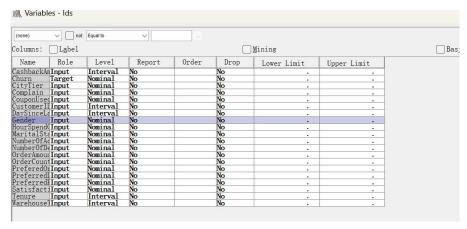
2.Creat Library and datasource



Drag the data source into a new diagram and perform operations.

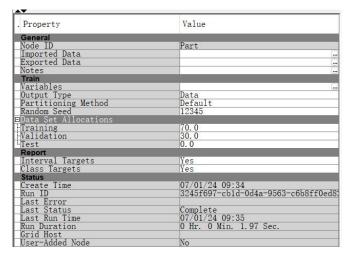


Right click on case_study and select Edit Variables. In order to pay attention to customer churn, I set "Churn" as the target variable.



2.Decision Tree Modelling using SAS Enterprise Miner

Create a Data Partition node and divide the data. 70% is used for train data and 30% is used for validation data.



Variable Summary

	Measurement	Frequency
Role	Level	Count
INPUT	INTERVAL	5
INPUT	NOMINAL	14
TARGET	NOMINAL	1

Partition Summary

		Number of
Туре	Data Set	Observations
DATA	EMWS2.Ids_DATA	3774
TRAIN	EMWS2.Part_TRAIN	2641
VALIDATE	EMWS2.Part_VALIDATE	1133

* Score Output

* Report Output

Summary Statistics for Class Targets

Data=DATA

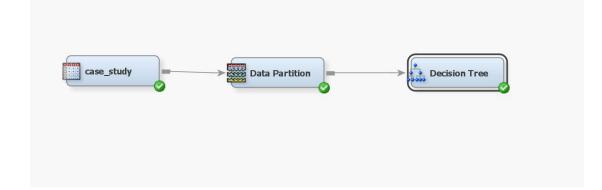
	Numeric	Formatted	Frequency		
Variable	Value	Value	Count	Percent	Label
Churn	0	0	3143	83.2803	Churr
Churn	1	1	631	16, 7197	Churr

Data=TRAIN

Numeric	Formatted	Frequency		
Value	Value	Count	Percent	Label
0	0	2199	83. 2639	Churn
1	1	442	16, 7361	Churn
	Value	Value Value	Value Value Count 0 0 2199	Value Value Count Percent 0 0 2199 83.2639

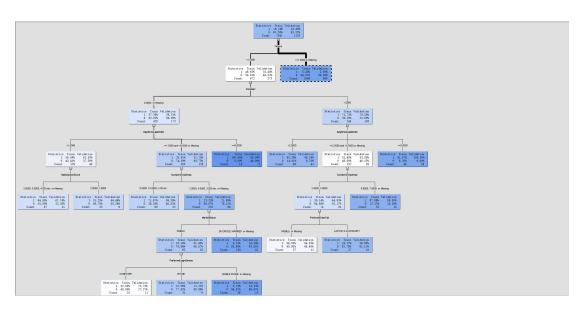
Data=VALIDATE

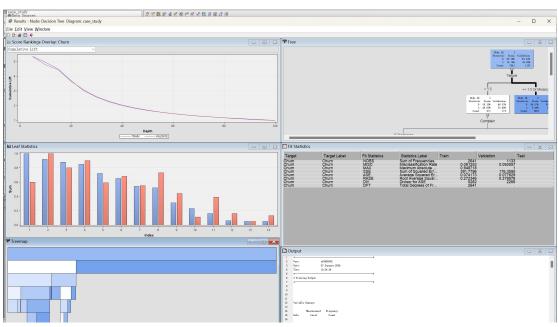
	Numeric	Formatted	Frequency		
Variable	Value	Value	Count	Percent	Label
Churn	0	0	944	83.3186	Churn
Churn	1	1	189	16.6814	Churn

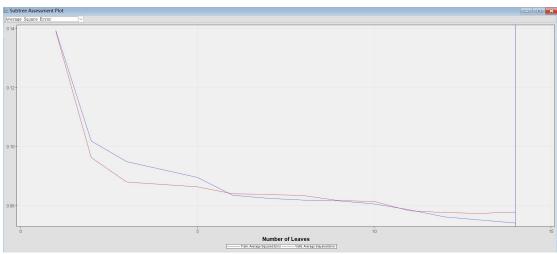


. Property	Value
General	
Node ID	Tree
Imported Data	
Exported Data	
Notes	
Train	
Variables	
Interactive	<u> </u>
Import Tree Model	No
Tree Model Data Set	
Use Frozen Tree	No
Use Multiple Targets	No
Splitting Rule	
Interval Target Criterion	ProbF
Nominal Target Criterion	ProbChisq
Ordinal Target Criterion	Entropy
Significance Level	0. 2
Missing Values	Use in search
Use Input Once	No
Maximum Branch	3
Maximum Depth	6
Minimum Categorical Size	5
Node	3
-Leaf Size	5
Number of Rules	5
Number of Surrogate Rules	0
Split Size	
Split Search	
Use Decisions	No
Use Priors	No
Exhaustive	5000
Node Sample	20000
Subtree	20000
Method	Assessment
Number of Leaves	1
Assessment Measure	Decision
Assessment Fraction	0. 25
Cross Validation	0.20
Perform Cross Validation	No
Number of Subsets	10
	1
Number of Repeats Seed	12345
Seed	12540

. Property	Value
-Use Input Once	No
-Maximum Branch	3
-Maximum Depth	6
Minimum Categorical Size	5
□Node	- 07 - 146
-Leaf Size	5
Number of Rules	5
Number of Surrogate Rules	0
-Split Size	
□Split Search	- 05 - 5-76
-Use Decisions	No
Use Priors	No
Exhaustive	5000
^L Node Sample	20000
□Subtree	
Method	Assessment
Number of Leaves	1
Assessment Measure	Decision
Assessment Fraction	0. 25
□Cross Validation	- A5
Perform Cross Validation	No
Number of Subsets	10
Number of Repeats	1
L Seed	12345
□Observation Based Importance	\(\text{\text{\$\frac{1}{2}}}\)
-Observation Based Importance	No
Number Single Var Importance	5
□P-Value Adjustment	W-
Bonferroni Adjustment	Yes
Time of Bonferroni Adjustment	Before
Inputs	No
Number of Inputs	1
Depth Adjustment	Yes
□Output Variables	
Leaf Variable	Yes
□Interactive Sample	
-Create Sample	Default
-Sample Method	Random
-Sample Size	10000
-Sample Seed	12345
Performance	Disk
at in the second	——————————————————————————————————————

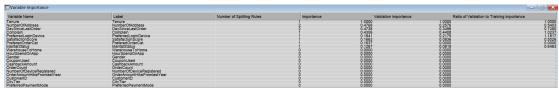






Fit Statistics							- 3
Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test	
Churn	Churn	NOBS	Sum of Frequencies		2641	1133	
Churn	Churn	MISC	Misclassification Rate	Q.	991253 948718 1,7796 1,74173 1,74246 5282 2,641	0.093557	
Churn	Churn	MAX	Maximum Absolute Error	0.	348718	1	
Churn	Churn	SSE	Sum of Squared Errors	35	1,7796	176.3595 0.077829 0.278978	
Churn	Churn	ASE RASE	Average Squared Error	0.	074173	0.077829	
Churn Churn Churn	Churn	RASE	Root Average Squared Error	0.	272346	0.278978	
Churn	Churn	DIV	Divisor for ASE Total Degrees of Freedom		5282	2266	
Churn	Churn	DFT					

Based on Fit Statistics, misclassification rate is 0.0912 for training dataset and 0.0935 for validation dataset.

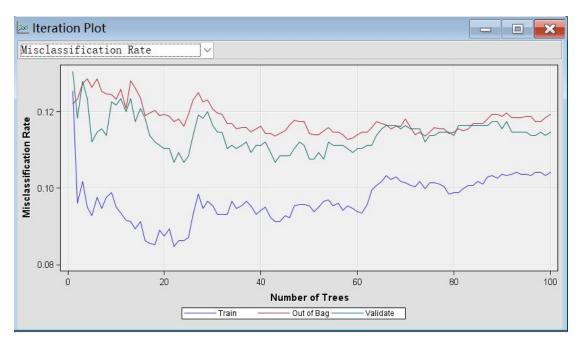


The Variable Importance Plot displays the importance of each predictor variable in the model. Only 8 out of 18 input variables are important to the pruned decision tree model.

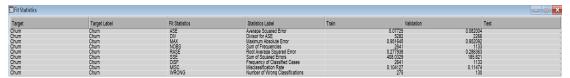
3.Ensemble Methods: Apply Bagging and Boosting, using the Random Forest algorithm as a Bagging example.

3.1 Using the Random Forest algorithm as a Bagging

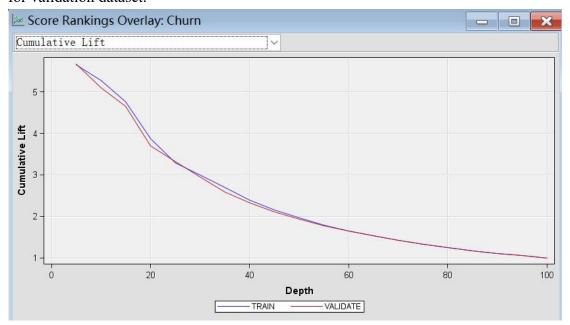
. Property	Value
General	
Node ID_	HPDMForest
Imported Data	
Exported Data	
Notes	
Train	
Variables	
□Tree Options	
Maximum Number of Trees	50
Seed	12345
Type of Sample	Proportion
Proportion of Obs in Each Sample	0. 6
Number of Obs in Each Sample	
□Splitting Rule Options	
Maximum Depth	50
Missing Values	Use In Search
Minimum Use In Search	1
Number of Variables to Consider in	
Significance Level	0.05
Max Categories in Split Search	30
Minimum Category Size	5
Exhaustive	5000
Node Options	D 6 14
Method for Leaf Size	Default
Smallest Percentage of Obs in Node	1. UE-5
Smallest Number of Obs in Node	
Split Size	V
Use as Modeling Node	Yes
Score	Wa-
Variable Selection	Yes Loss Reduction
Variable Importance Method	
Number of Variables to Consider Cutoff Fraction	0.01
CONTRACTOR	0.01
Status Create Time	07/01/24 10:14
Run ID	07/01/24 10.14
Last Error	
Last Status	
Last Status Last Run Time	
Run Duration	
Grid Host	
User-Added Node	No
ozer yadea yode	μvo



Based on Iteration Plot, misclassification rate plateaued out when number of trees reaches 25.

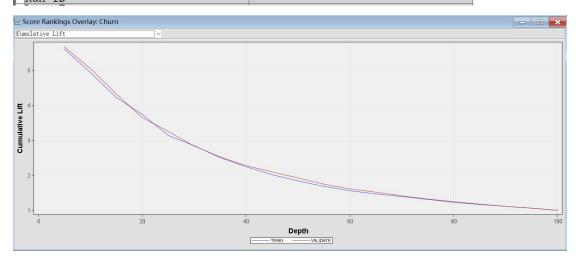


Based on Fit Statistics, misclassification rate is 0.1041 for training dataset and 0.1147 for validation dataset.



3.2 Gradient Boosting

. Property	Value
General	150-1
Node ID	Boost
Imported Data	
Exported Data	
Notes	
Train	
Variables	
□Series Options	
N Iterations	50
Seed	12345
Shrinkage	0. 1
Train Proportion	60
□Splitting Rule	
Huber M-Regression	No
Maximum Branch	2
Maximum Depth	2
Minimum Categorical Size	2 5
Reuse Variable	1
-Categorical Bins	30
-Interval Bins	100
Missing Values	Use in search
-Performance	Disk
□Node	- Anna Carlo
-Leaf Fraction	0. 1
Number of Surrogate Rules	0
LSplit Size	
□Split Search	
Exhaustive	5000
Node Sample	20000
■Subtree	1.000 - 100 -
Assessment Measure	Decision
Score	And the second s
Subseries	Best Assessment Value
Number of Iterations	1
Create H Statistic	No
Variable Selection	Yes
Report	90 (90 C)
Observation Based Importance	No
Number Single Var Importance	5
Status	
Create Time	07/01/24 10:21
Run ID	



_						
Variable Importance						- D X
Variable Name	Label	Number of Splitting Rules	Importance	Validation Importance	ce Ratio of Validat	ion to Training Importance
Tenure	Tenure		22	1	1	1
Complain NumberOfAddress	Complain		14	0.365652	0.377918	1.033547
NumberOfAddress	NumberOfAddress		23	0.288403	0.149877	0.519679
DaySinceLastOrder PreferedOrderCat MaritalStatus	DaySinceLastOrder PreferedOrderCat MaritalStatus		6	0.355652 0.288403 0.248446 0.181082 0.160293 0.14942 0.123483 0.121687	0.377918 0.149877 0.217875 0.133927 0.139935	1.03364 0.519675 0.876602 0.739593 0.87296
PreferedOrderCat	PreferedOrderCat		7	0.181082	0.133927	0.739593
WarehouseToHome	WarehouseToHome		3	0.160299	0.139935	0.87295
OrderAmountHikeFromlastYear	vvarenouse i oHome OrderAmountHikeFromlastYear		5	0.155695	<u> </u>	
OrderCount OrderCount	OrderCount OrderCount		2	0.14942	0	
OrderCount	OrderCount		2	0.123403	y .	
Droforred Daymonth fode	Droformed Daymonth Lordo		2	0.121007	, and the second	}
NumberOfDevise Registered	CityTier PreferredPaymentMode NumberOfDeviceRegistered		-	0.110447 0.047227	0.068239	1,444936
CityTier PreferredPaymentMode NumberOfDeviceRegistered CouponUsed CashbackAmount	Counon liead		1	0.035711	0.000239	1.44400
CashbackAmount	CouponUsed CashbackAmount		ó	0.000111	ň	,
	HourSpendOnApp		Ď.	ŏ	ŏ	
Gender	Gender		Ō	ŏ	ŏ	
Preferred painDevice	PreferredLoginDevice		ō	ō	ō	
CustomeriD	CustomerID SatisfactionScore		0	Ō	ō	
SatisfactionScore	SatisfactionScore		0	0	0	

It can also be seen that the most important variable of the Boosting model is Tenure. A total of 13 variables are used by the Boosting model.

Variable Summary

	Measurement	Frequency
Role	Level	Count
ID	INTERVAL	1
INPUT	INTERVAL	5
INPUT	NOMINAL	14
TARGET	NOMINAL	1

Model Events

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

Predicted and decision variables

Туре	Variable	Label
TARGET	Churn	Churn
PREDICTED	P_Churn1	Predicted: Churn=1
RESIDUAL	R_Churn1	Residual: Churn=1
PREDICTED	P_ChurnO	Predicted: Churn=0
RESIDUAL	R_ChurnO	Residual: Churn=0
FROM	F_Churn	From: Churn
INTO	I_Churn	Into: Churn

Fit Statistics

Target=Churn Target Label=Churn

Fit			
Statistics	Statistics Label	Train	Validation
NOBS	Sum of Frequencies	2641.00	1133.00
SWWW	Sum of Case Weights Times Freq	5282.00	2266.00
MISC	Misclassification Rate	0.10	0.10
MAX	Maximum Absolute Error	0.97	0.97
SSE	Sum of Squared Errors	426, 49	182.28
ASE	Average Squared Error	0.08	0.08
RASE	Root Average Squared Error	0.28	0.28
DIV	Divisor for ASE	5282.00	2266.00
DFT	Total Degrees of Freedom	2641.00	100

Assessment Score Rankings

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

							Mean
			Cumulative	%	Cumulative	Number of	Posterior
Depth	Gain	Lift	Lift	Response	% Response	Observations	Probability
5	461.571	5. 61571	5. 61571	93, 9850	93, 9850	133	0.66686
10	393, 792	4.25500	4.93792	71.2121	82.6415	132	0.55615
15	322.924	2.80649	4.22924	46.9697	70. 7809	132	0.47382
20	273, 868	2.26330	3. 73868	37, 8788	62.5709	132	0.37317
25	213.671	0.72426	3.13671	12.1212	52.4962	132	0.26800
30	184.063	1.35798	2.84063	22. 7273	47.5410	132	0.18228
35	150.632	0.49793	2.50632	8.3333	41.9459	132	0.13070
40	123.855	0.36213	2. 23855	6.0606	37.4645	132	0.10457
45	101.516	0.22633	2.01516	3. 7879	33. 7258	132	0.08877
50	83.641	0.22633	1.83641	3, 7879	30. 7343	132	0.07775
55	68. 191	0.13580	1.68191	2.2727	28.1487	132	0.06842
60	55, 315	0.13580	1.55315	2.2727	25.9937	132	0.06153
65	46.159	0.36213	1.46159	6.0606	24.4613	132	0.05573
70	38.633	0.40739	1.38633	6.8182	23.2017	132	0.05026
75	30, 300	0.13580	1.30300	2.2727	21.8072	132	0.04457
80	22.443	0.04527	1.22443	0. 7576	20.4922	132	0.03866
85	16.308	0.18106	1.16308	3.0303	19.4655	132	0.03231
90	11.106	0.22633	1.11106	3, 7879	18.5949	132	0.02724
95	5.261	0.00000	1.05261	0.0000	17.6166	132	0.02326
100	0.000	0.00000	1.00000	0.0000	16, 7361	132	0.01841

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

Posterior	Number		Mean	
Probability	of	Number of	Posterior	
Range	Events	Nonevents	Probability	Percentage
0. 75-0. 80	2	0	0. 76298	0.0757
0.70-0.75	31	1	0. 72228	1.2117
0.65-0.70	46	1	0.66991	1.7796
0.60-0.65	55	8	0.62213	2.3855
0.55-0.60	40	14	0.57674	2.0447
0.50-0.55	64	24	0.52597	3, 3321
0.45-0.50	33	45	0.47839	2.9534
0.40-0.45	26	39	0.43024	2.4612
0.35-0.40	24	38	0.37371	2.3476
0.30-0.35	13	41	0.32747	2.0447
0.25-0.30	5	63	0.27885	2.5748
0.20-0.25	17	60	0.23024	2.9156
0.15-0.20	21	81	0.17276	3.8622
0.10-0.15	16	217	0.12050	8,8224
0.05-0.10	31	728	0.06993	28, 7391
0.00-0.05	18	839	0.03212	32.4498

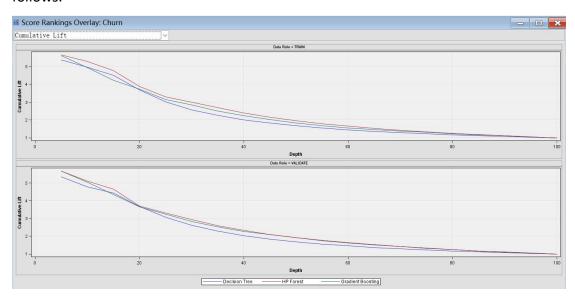
As can be seen from the above figure, the misclassification rate is only 0.1, so the model has better effect.

4. Compare models

Use the model comparison node Model Compare to compare the results of the three models. The result is as follows:

. Property	Value
General	W.C.
Node ID	MdlComp
Imported Data	
Exported Data	
Notes	
Train	
Variables	
∃Assessment Reports	
Number of Bins	20
-ROC Chart	Yes
1. Recompute	No
■Model Selection	
Selection Data	Default
Selection Statistic	Misclassification Rate
HP Selection Statistic	Default
SAS Viva Selection Statistic	
Selection Table	Train
Selection Depth	10
Score	
Selection Editor	
Report	
■Selected Model	
Target	Churn
Model Node	Tree
Model Description	Decision Tree
Selection Criteria	Valid: Misclassification Rate
Status	
Create Time	07/01/24 10:33
Run ID	9d98d678-f71e-2148-9890-9a15f031e5
Last Error	
Last Status	Complete
Last Run Time	07/01/24 11:07
Run Duration	0 Hr. 0 Min. 4.96 Sec.
Grid Host	2 111
User-Added Node	No

The above is the setting process of the model comparison node. The misclassification rate is selected as the criterion for selecting the best model. The results are as follows:



Fit Statistics
Model Selection based on Valid: Misclassification Rate (_VMISC_)

				Train:		Valid:
			Valid:	Average	Train:	Average
Selected			Misclassification	Squared	Misclassification	Squared
Model	Model Node	Model Description	Rate	Error	Rate	Error
У	Tree	Decision Tree	0. 09356	0.074173	0.09125	0.077829
	Boost	Gradient Boosting	0.09532	0.080744	0.09542	0.080441
	HPDMForest	HP Forest	0.11474	0.077250	0.10413	0.082004

As can be seen from the figure, the misclassification rate of Decision tree is 0.0912, boost is 0.0954, and bagging is 0.1041. The Decision Tree has the lowest misclassification rate (0.0912), making it the best-performing model among the three based on the given metric. Lower misclassification rates usually suggest better predictive performance.

Examining decision tree and ensemble models, specifically in the context of customer behavior, offers valuable insights for shaping business strategies. The Decision Tree model, boasting low Root Average Squared Error (RASE) and Sum of Squared Errors (SSE), lays a robust foundation for comprehending factors influencing customer loyalty and churn. Crucial factors like "Tenure," "Preferred Login Device," and "Satisfaction Score" emerge as pivotal in shaping customer decisions. Meanwhile, the Boosting model, despite slightly higher RASE and SSE, delves into nuanced patterns, adding depth to the analysis. On the contrary, the HPDM, likely a hyperparameter-tuned Decision Tree, presents higher complexity with an elevated RASE, prompting careful consideration.

Strategic recommendations involve prioritizing insights from the Decision Tree, harnessing the nuanced findings of the Boosting model, and thoughtfully evaluating the benefits of hyperparameter tuning. Businesses can refine customer retention strategies, tailor promotions based on factors like "Coupon Usage" and "Order Frequency," and implement targeted engagement approaches, taking into account "Days Since Last Order."

In essence, a thorough examination of decision tree and ensemble models equips businesses with actionable insights to elevate customer retention strategies, optimize promotional initiatives, and enhance overall customer engagement.