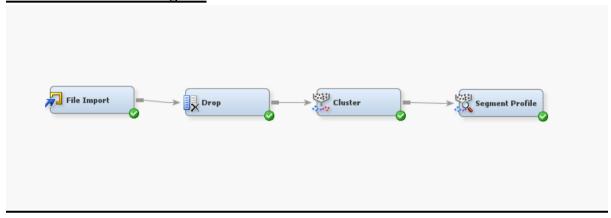
#### Objective 1:Identify the most profitable customer segment.

#### **Purpose:**

Identify high-value customer segment based on past purchase history. High-value customers represent the most profitable group to receive targeted marketing attention for their current and future value to the business. This will allow us to focus marketing efforts on the most profitable segments. The key advantage of focusing on high-value segments is marketing efficiency - effort and resources can be concentrated on the subset of customers that provide the largest profits.

#### Overview of the EM diagram



#### **Methodology- Cluster analysis**

The raw dataset contains a lot of irrelevant variables. Then, we need to drop some irrelevant variables like <code>Days\_to\_Ship</code> Actually, <code>Ship\_Status</code>, <code>Category</code>, <code>Country</code>, <code>Order\_Date</code>, <code>Order\_ID</code>, <code>City</code>, <code>Postal\_Code</code>, etc.. <code>Customer\_name</code> and <code>Sales\_per\_Customer</code> are the input variables for clustering.

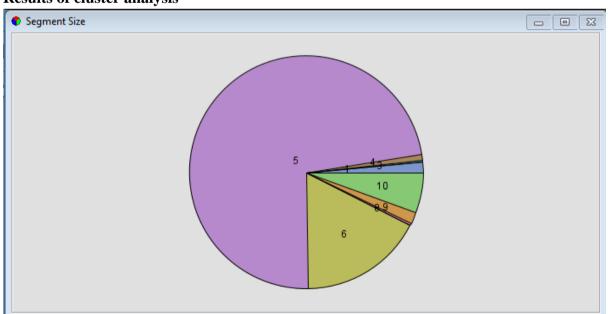
# Input Variables:

# Customer\_name and Sales\_per\_Customer.

Name	Drop	Role	Level		
Category	Yes	Input	Nominal		
City	Yes	Input	Nominal		
Country	Yes	Input	Nominal		
Customer_Name	No	Input	Nominal		
Days_to_Ship_A	Yes	Input	Interval		
Days_to_Ship_S	Yes	Input	Interval		
Discount	Yes	Input	Interval		
Number_of_Rec	Yes	Input	Interval		
Order_Date	Yes	Input	Nominal		
Order_ID	Yes	Input	Nominal		
Postal_Code	Yes	Input	Interval		
Product_Name	Yes	Text	Nominal		
Profit	Yes	Input	Interval		
Profit_Ratio	Yes	Input	Interval		
Profit_per_Orde	Yes	Input	Interval		
Quantity	Yes	Input	Interval		
Region	Yes	Input	Nominal		
Sales	Yes	Input	Interval		
Sales_Forecast	Yes	Input	Interval		
Sales_per_Custo	No	Input	Interval		
Satisfaction	Yes	Input	Interval		
Segment	Yes	Segment	Nominal		
Ship_Date	Yes	Input	Nominal		
Ship_Mode	Yes	Input	Nominal		
Ship_Status	Yes	Input	Nominal		
State	Yes	Input	Nominal		
Sub_Category	Yes	Input	Nominal		

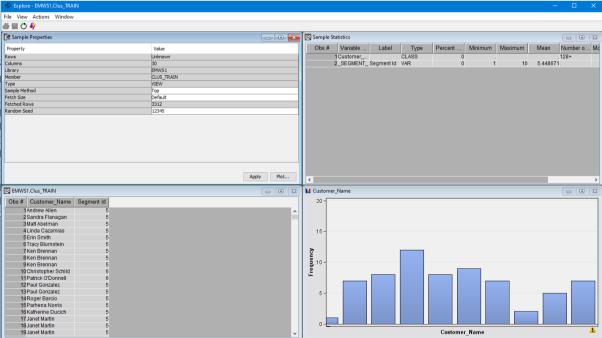
# **Findings**

# Results of cluster analysis

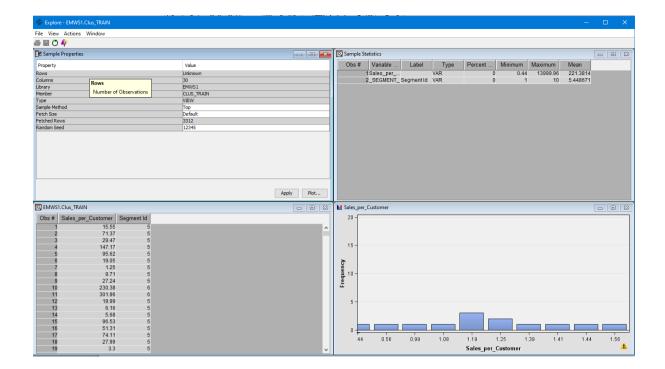


There are 10 clusters representing 10 different groups of spending.





**Segment profiling of sales per customers:** 



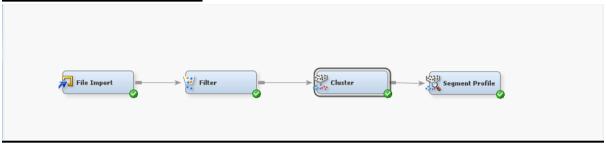
# conclusion:

focus on  $\mbox{marketing the highest percentage of the group (group 5).}\ 72.7\%$  , rest are non-profitable customers.

#### **Objective 2: Identify the seasonal product.**

For developing the tailored-marketing strategy, companies should familiarize with the top-sellers in various time-slots, i.e. seasons. Firstly, we should identify different types of products sold in the given time period. Therefore, we can spot the best seller in different seasons. Observations with similar characteristics would be grouped into the same segment by using cluster analysis.

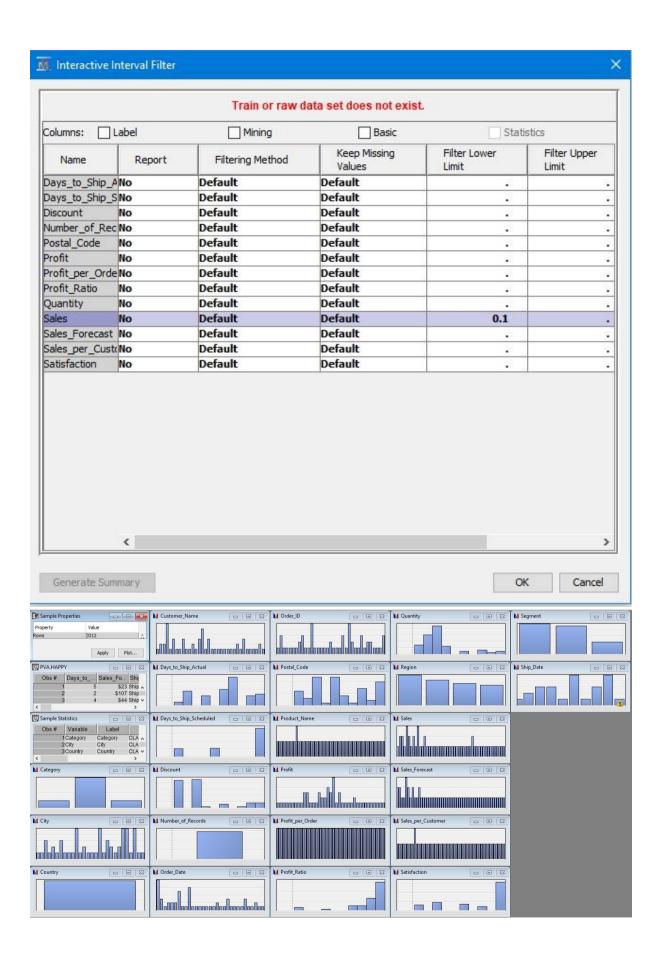
#### Overview of the EM diagram



#### 2.1 Methodology

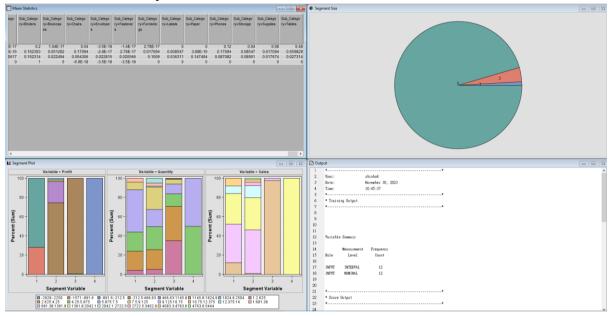
Firstly, we do data cleansing in order to eliminate the missing values. We set the user-specific for class variable in the filter: Category, City, Country, Custer name, Order date, order ID, region, segment, ship date, ship mode, ship status, state, sub category. And then, we also set the user-specific interval variables: day to ship actual, day to ship scheduled, discount, number of records, postal code, profit, profit ratio, profit per order, quantity, sales, sales forecast, sales per customer. Also, we set the lower limit for Sales is 0.1 as companies will not generate zero sales in each sales record.

Name	Use	Report	Role	Level
City	No	No	Input	Nominal
Country	No	No	Input	Nominal
Customer_Name	No	No	Input	Nominal
Days_to_Ship_A	No	No	Input	Interval
Days_to_Ship_S	No	No	Input	Interval
Discount	No	No	Input	Interval
Number_of_Rec	No	No	Input	Interval
Order_Date	Default	No	Input	Nominal
Order_ID	No	No	Input	Nominal
Postal_Code	No	No	Input	Interval
Profit	Default	No	Input	Interval
Profit_Ratio	No	No	Input	Interval
Profit_per_Orde	No	No	Input	Interval
Quantity	Default	No	Input	Interval
Region	No	No	Input	Nominal
Sales	Default	No	Input	Interval
Sales_Forecast	No	No	Input	Interval
Sales_per_Custo	No	No	Input	Interval
Segment	Default	No	Input	Nominal
Ship_Date	No	No	Input	Nominal
Ship_Mode	No	No	Input	Nominal
Ship_Status	No	No	Input	Nominal
State	No	No	Input	Nominal
Sub_Category	Default	No	Input	Nominal



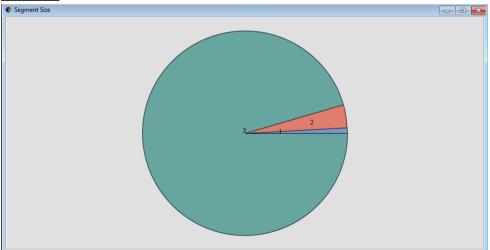
## 2.2 Findings

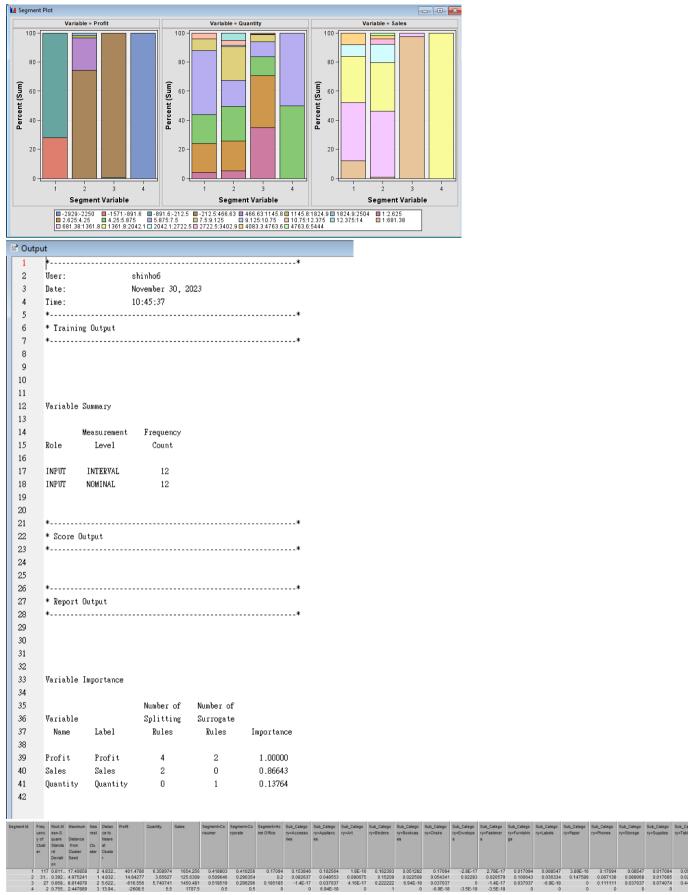
#### Results of cluster analysis



After data cleansing, we investigate the result by the order date. There are 4 clusters representing 4 different seasons. Hence, we will focus on analyzing these four groups.

## Cluster 1





Segment 1 generated \$1654.256 total sales. In this segment consumers and corporate buy most as they shared the biggest proportion in this segment. The category of accessories,

binders, chairs and phones shared the highest frequency from the statistical table. Therefore, the products in accessories, binders, chairs and phones group is the best-sellers in this season. This season is heavily impacted by the festivals, like Christmas, New Years Holiday. As we need to buy some accessories to decorate and buy new chairs during the New Years Holiday. Also, the sales revenue is quite optimistic during these festivals.

Segment 2 generated \$125.6309total sales. It is quite a disaster for this segment as it has the lowest sales volume among all segments. In this segment consumers buy most. The category of binders, furnishing, and paper shared the highest frequency from the statistical table. Therefore, the products in the tables group is the best-sellers in this season. We predict this is the season of Autumn as the category of Paper shares the highest proportion. It is not affected by any special festivals.

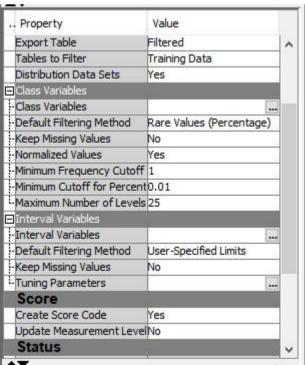
Segment 3 generated \$1450.481 total sales. In this segment consumers also buy most as it shares the biggest proportion in this segment. The category of binders, tables and phones shared the highest frequency from the statistical table. Here we predicted that segment 3 is summer as the demand for tables is extremely huge. Before getting into September, students may purchase a new table and chair for a new semester.

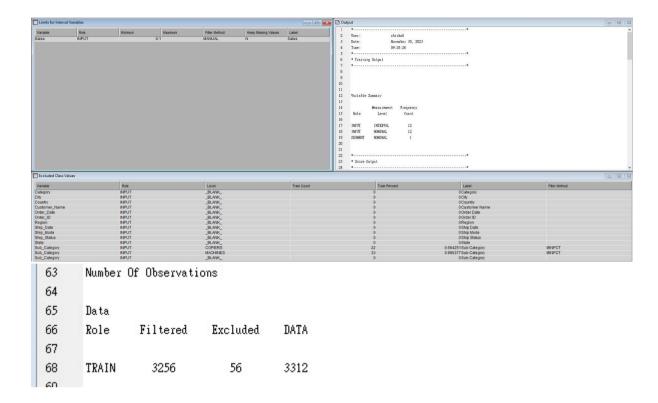
Segment 4 generated \$1707.5 total sales, In this segment consumers and corporate also buy most as they shared the same proportion in this segment. The category of binders dominated in this segment, it shows 1 in this category group. So, we assume this segment is spring.

#### **Objective 2 Setting:**

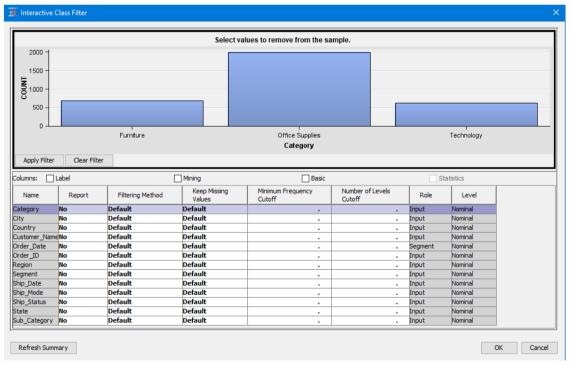
#### 2.1 Data preparation

#### 2.1.1 Filter

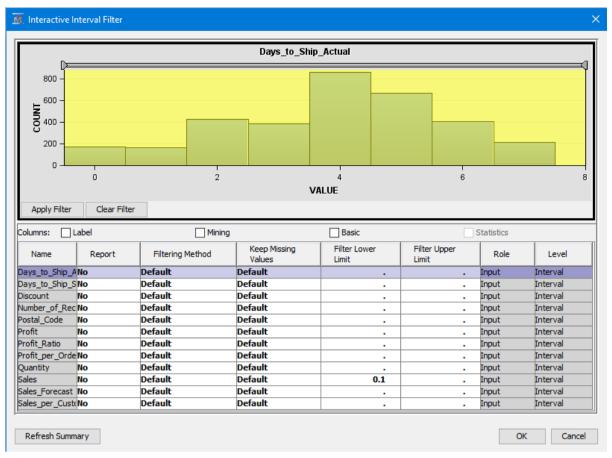




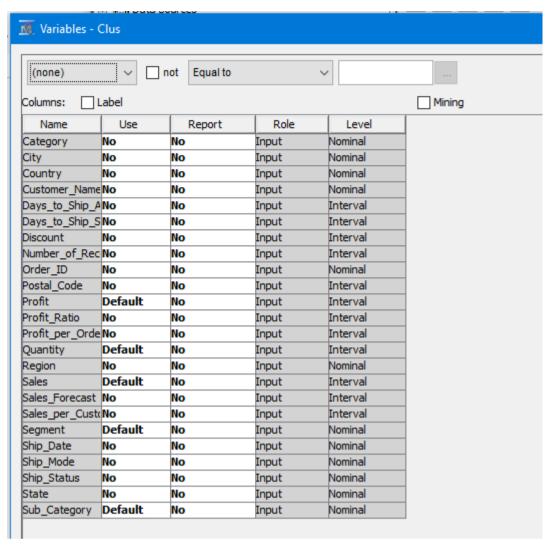
#### Class variable



Interval variable

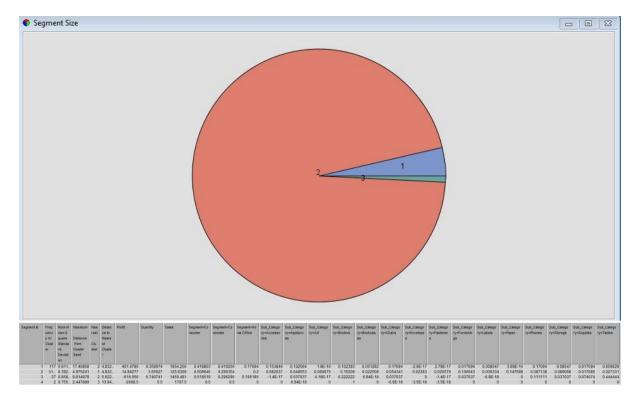


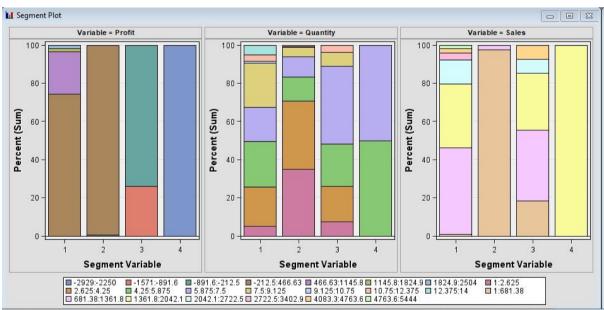
• Cluster 1



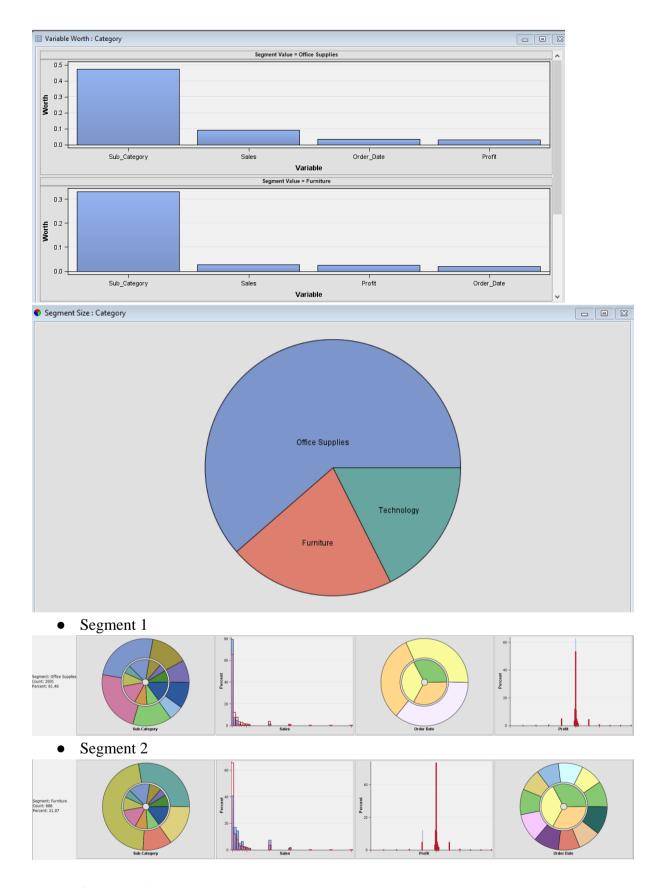
#### 2.2 Cluster Result

• Cluster1

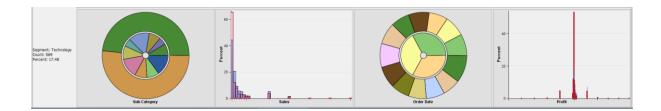




Product Type



• Segment 3



## Objective 3: Analysis customer preference for shipping

Purposes: Finding which factors affect the customer preference on selecting shipping mode(method)

# 3.1 Data Preparation



# 3.1.1 File Import

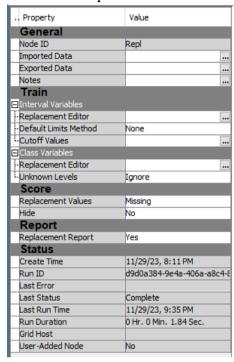
	-	
Name	Role 🛆	Level
Order_ID	ID	Nominal
Segment	Input	Ordinal
Discount	Input	Interval
Region	Input	Ordinal
Quantity	Input	Interval
Sales	Input	Interval
City	Input	Ordinal
Sub_Category	Input	Ordinal
Category	Input	Ordinal

Input variable {Segment, Discount, Region, Quantity, Sales, City, Sub\_Category, Category}

Target variable {Ship\_Mode}

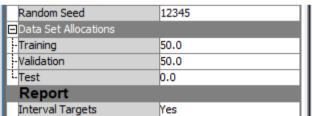
#### 3.1.2 Replacement

Since suppose the Sales should not be zero, it is an unreasonable data. Hence we would like to replace Sales with zero value missing. And set 1 as the lower limit field for Sales in the Interactive Replacement Interval Filter.



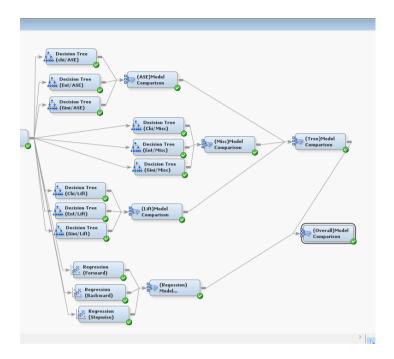
#### 3.1.3 Data Partition

The data is split into 2 data sets, which is the Training and Validation data set. The proportion was set to be 50% each.



#### 3.2 Methodolgy

We chose to use regression and decision trees to build different models and consider which has the best model by comparing with misclassification rate.



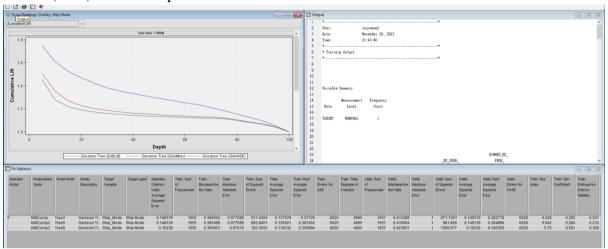
## 3.2.1 Decision tree

5.2.1 Decision tree	į vo	
☐Splitting Rule		
-Interval Target Criterion	ProbF	
-Nominal Target Criterion	ProbChisq	
_	Entropy	
-Significance Level	0.2	
-Missing Values	Use in search	
-Use Input Once	No	
-Maximum Branch	8	
-Maximum Depth	6	
Minimum Categorical Size	5	
⊟Node		
-Leaf Size	5	
-Number of Rules	5	
-Number of Surrogate Rules	0	
i-Split Size		
⊟Split Search		
-Use Decisions	No	
-Use Priors	No	
-Exhaustive	5000	
Node Sample	20000	
□Subtree		
-Method	Assessment	
-Number of Leaves	1	
-Assessment Measure	Average Square Error	
Assessment Fraction	0.25	
□Cross Validation		
	No	
-Number of Subsets	10	
-Number of Repeats	1	м
Seed	12345	*

- data are build with different criterion and assessment measure

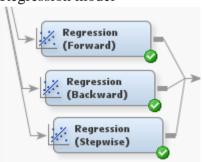


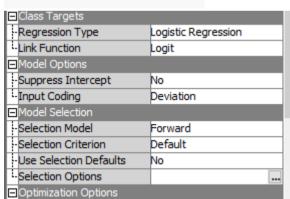
- (ASE) model comparision

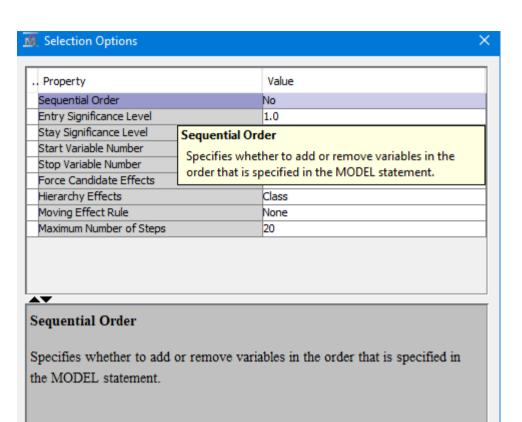


- (Tree) model comparison

## Regression model



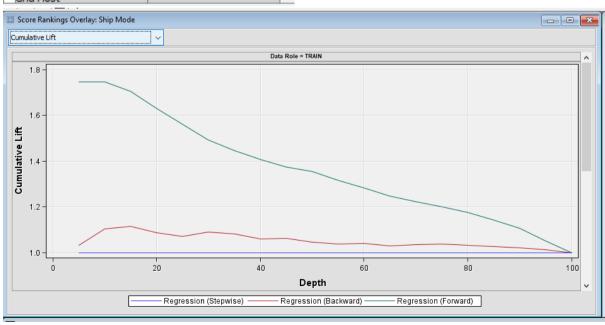




OK

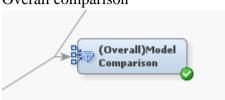
Cancel

Property	Value	
General		^
Node ID	MdlComp5	
Imported Data		
Exported Data		
Notes		
Train		
Variables		
Assessment Reports		
Number of Bins	20	
ROC Chart	Yes	
i. Recompute	No	
■Model Selection		
-Selection Data	Default	
-Selection Statistic	Average Squared Error	
HP Selection Statistic	Default	
SAS Viya Selection Statistic		
Selection Table	Validation	
Selection Depth	10	
Score		
Selection Editor		
Report Selected Model		
Target	Ship_Mode	
-Model Node	Reg	
-Model Description	Regression (Forward)	
Selection Criteria	Valid: Average Squared Err	
Status		
Create Time	11/29/23, 9:46 PM	
Run ID	f4e05b61-c9db-43bf-82b1-	
Last Error		
Last Status	Complete	
Last Run Time	11/29/23, 10:31 PM	
Run Duration	0 Hr. 0 Min. 3.39 Sec.	
Grid Host		٧
<del></del>		

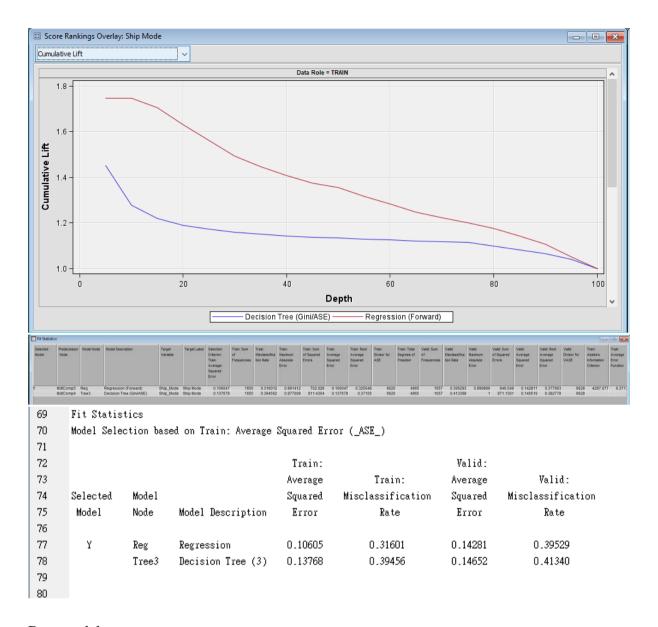


Fit Statistic	G .																							
Selected ifodel	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Valid:	Train: Akaike's Information Criterion		Train: Average Error Function	Train: Degrees of Freedom for Error	Train: Model Degrees of Freedom	Train: Total Degrees of Freedom	Train. Divisor for ASE	Train: Error Function	Train: Final Prediction Error	Train: Maximum Absolute Error	Train: Mean Square Error	Train: Sum of Frequencies	Train: Number of Estimate Weights	Train: Root Average Sum of Squares	Train: Root Final Prediction Error	Train: Root Mean Squared Error	Train: Schwarz's Bayesian Criterion	Train: Sum of Squared Errors
	Reg3	Reg3	Regression. Regression. Regression.	Ship_Mode	Ship Mode	0.142811 0.149906 0.150808	4297.077 3663.887 3660.192	0.149898	0.371764 0.552551 0.544742	4962	3	4965	662	3657.88	7 0.15007	0.943807	0.130102 0.149988 0.14939	1655 1655 1655		0.38716	0.3874	0.387283		992.3215

# Overall comparison



Property	Value	
General		٨
Node ID	MdlComp6	
Imported Data		
Exported Data		
Notes		
Train		
Variables		
☐ Assessment Reports		
-Number of Bins	20	
-ROC Chart	Yes	
iRecompute	No	
■ Model Selection		
-Selection Data	Default	
-Selection Statistic	Average Squared Error	
HP Selection Statistic	Default	
-SAS Viya Selection Statistic		
-Selection Table	Train	
Selection Depth	10	
Score		
Selection Editor		
Report		
☐Selected Model		
Target	Ship_Mode	
-Model Node	Reg	
-Model Description	Regression	
E-Selection Criteria	Train: Average Squared Err	
Status		
Create Time	11/29/23, 9:57 PM	
Run ID	a5005d17-c1ac-43d4-a4ee	
Last Error		
Last Status	Complete	
Last Run Time	11/29/23, 10:00 PM	
Run Duration	0 Hr. 0 Min. 3.42 Sec.	
Grid Host		٧

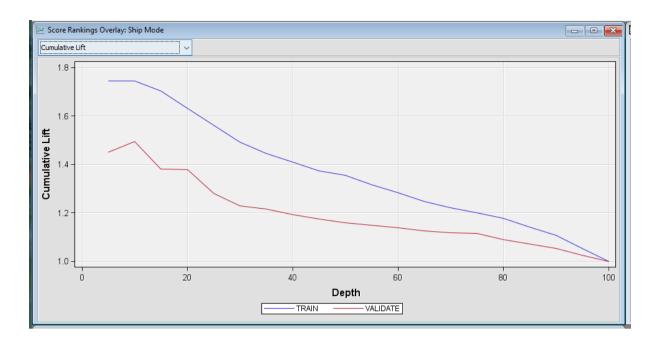


## Best model

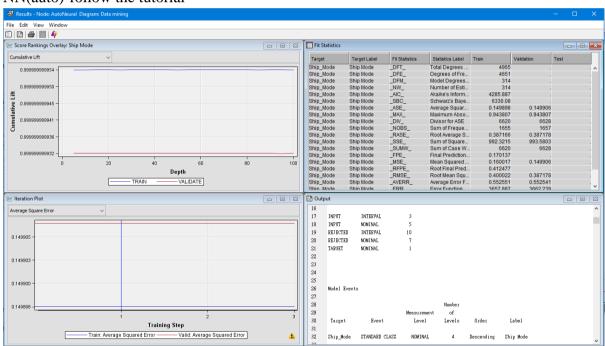
## (regression forward)

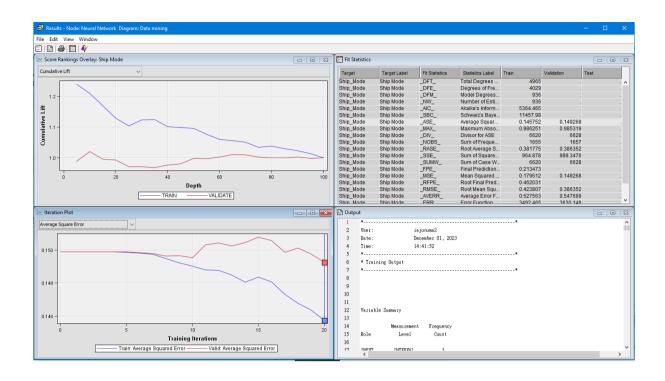
Type 3 Analysis of Effects

		Wald	
Effect	DF	Chi-Square	Pr > ChiSq
Category	6	7.3814	0.2870
City	842	417.4008	1.0000
Discount	3	1.9610	0.5806
Quantity	3	8.6327	0.0346
Region	9	15.1936	0.0858
Sales	3	1.4217	0.7004



## NN(auto)-follow the tutorial





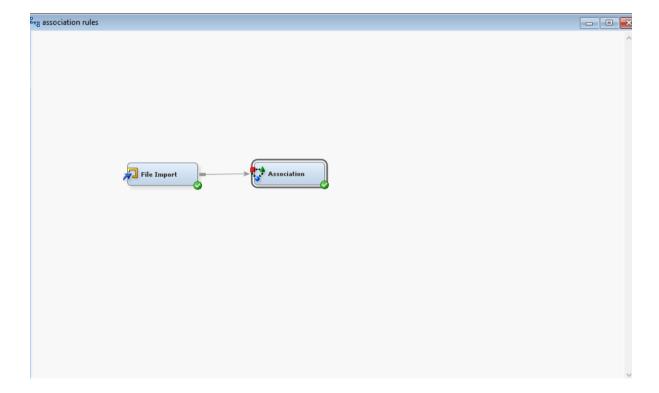
Objective 4: Identify shipping lanes with repeated delays.

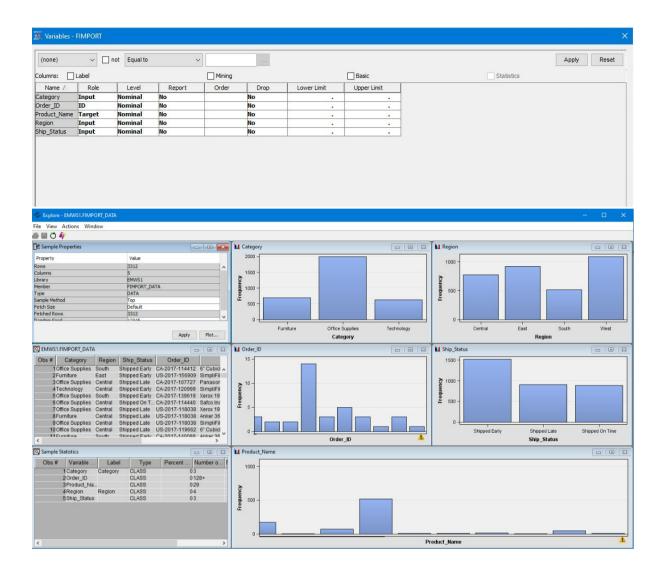
#### Purpose:

Identify shipping lanes with repeated delays based on the shipping preference and shipping status. To collect the customer information through interactions to reach our purposes, such as demographic information, purchasing behavior, and geographic information. Therefore, the company could give a better prediction to consumers to predict when they would receive their package. In the long term, this will reduce customer dissatisfaction and attract them to consume more in our company.

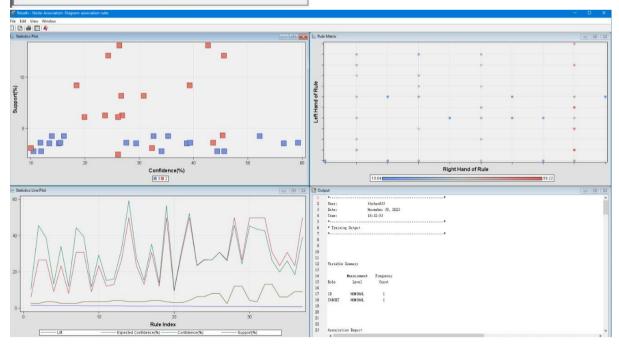
Methodology:

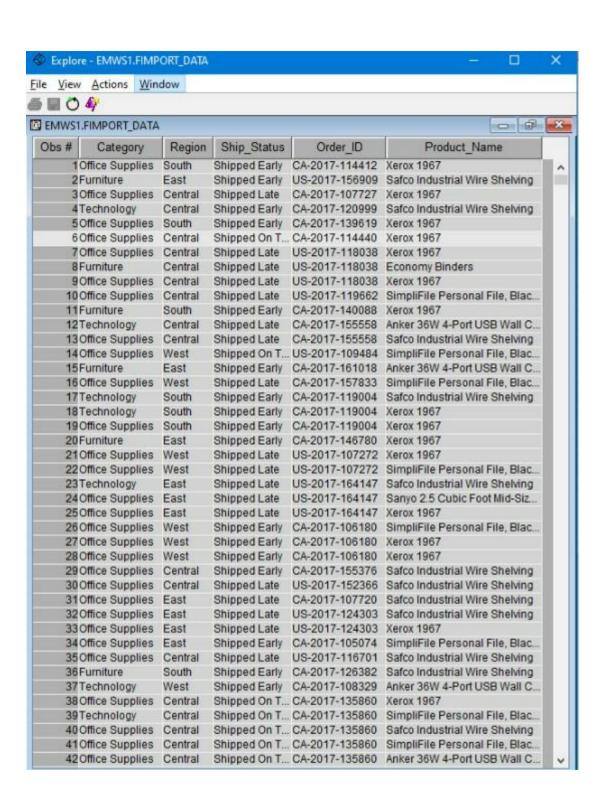
Input Variables: Product categories, region, ship status, order ID, product name



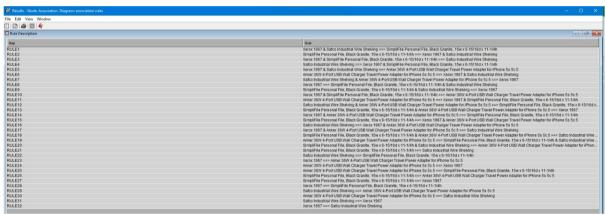


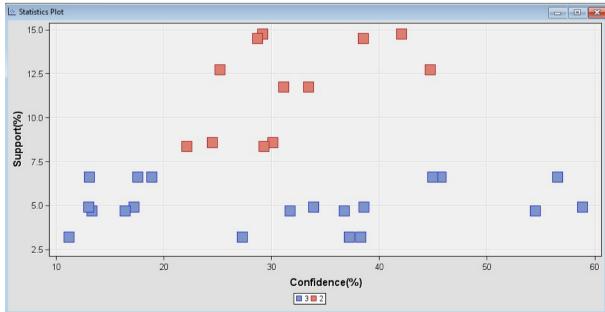
. Property	Value	
General	1100000	
Node ID	FIMPORT	
Imported Data		
Exported Data		
Notes		
Train		
Variables		
Import File	C:\Users\thchan433\Docu	Ī
Maximum Rows to Import	1000000	
Maximum Columns to Import	10000	
Delimiter	,	
Name Row	Yes	
Number of Rows to Skip	0	
Guessing Rows	500	
File Location	Local	
File Type	xlsx	
Advanced Advisor	No	
Rerun	No	
Score		
Role	Transaction	
Report		
Summarize	No	
Status		
Create Time	11/30/23, 4:29 PM	
Run ID		
Last Error		
Last Status	1	
Last Run Time		ĺ
Run Duration		ĺ
Grid Host		ĺ
User-Added Node	No	

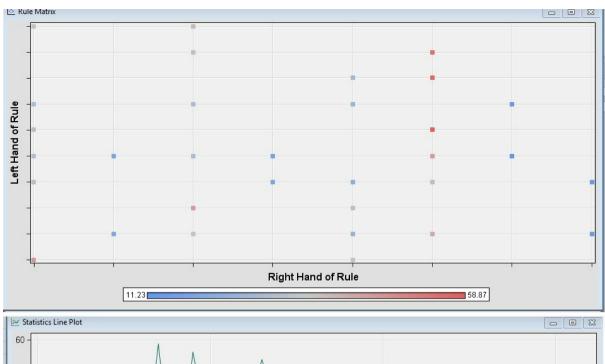


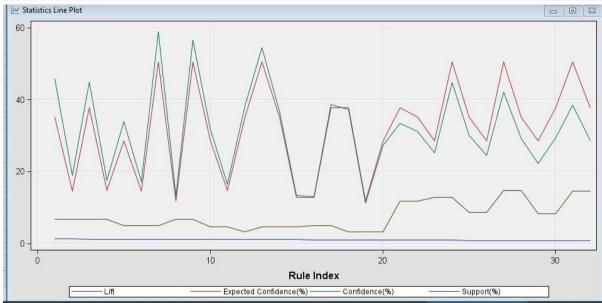


Ruis Table													
	Left Hand of Rule	Right Hand of Rule	Rule item	Rule item 2	Rule tem 3	Rule item 4	Rule item 5	Rule Index	Transpos e Rule				
ndustrial Wire Shelving & Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> Xerox 1967				Anker 36					/ 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h & Safco Industrial Wire Shehing ==> Xerox 1967				Safco In				1	3 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h & Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> Xerox 1967				Anker 36				- 1	3 1				
967 & Safco Industrial Wire Shelving ==> SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h				Safco In					1 1				
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ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h ==> Xerox 1967								2					
967 & Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> Safco Industrial Wire Shelving				Anker 36		Safco In		1					
ndustrial Wire Shelving ==> Xerox 1967								3					
ndustrial Wire Shelving & Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h				Anker 36				1					
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967 & Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h				Anker 36				1	4 1				
967 & Safco Industrial Wire Shehing ==> Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5				Safco In		Anker 36			5 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h ==> Safco Industrial Wire Shelving								2					
967 & Simplifile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h ==> Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5				SimpliFil		Anker 36		1					
ndustrial Wire SheMing ==> SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h								2					
6W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h								2					
6W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> Safco Industrial Wire Shelving	Anker 3	Safco In	Anker 36.		Safco In_			3	.0 1				
967 ==> SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h	Xerox 1	SimpliFil.	Xerox 19		SimpliFil			2	.6 1				
967 ==> Safco Industrial Wire Shelving	Xerox 1	Safco In	Xerox 19		Safco In			3	2 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h & Safco Industrial Wire Shelving ==> Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5	SimpliFi.	Anker 36	Simplifil	Safco In		Anker 36		2	.0 1				
967 xxx Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5	Xerox 1	Anker 36.	Xerox 19.	DESCRIPTION.	Anker 36			2	.3 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h ==> Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5	SimpliFi.	. Anker 36.	Simplifil		Anker 36			2	6 1				
ndustrial Wire Shelving ==> Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5	Safco In	Anker 36	Safco In		Anker 36			2	9 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h ==> Xerox 1967 & Safco Industrial Wire Shelving	SimpliFi.	Xerox 19.	Simplifil		Xerox 19	Safco In			2 1				
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6W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5 ==> Xerox 1967 & SimpliFile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h								1	1 1				
ile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h ==> Xerox 1967 & Anker 36W 4-Port USB Wall Charger Travel Power Adapter for iPhone 5s 5c 5								1	5 1				
967 ==> Simplifile Personal File, Black Granite, 15w x 6-15/16d x 11-1/4h & Safco Industrial Wire Shelving				******					8 1				
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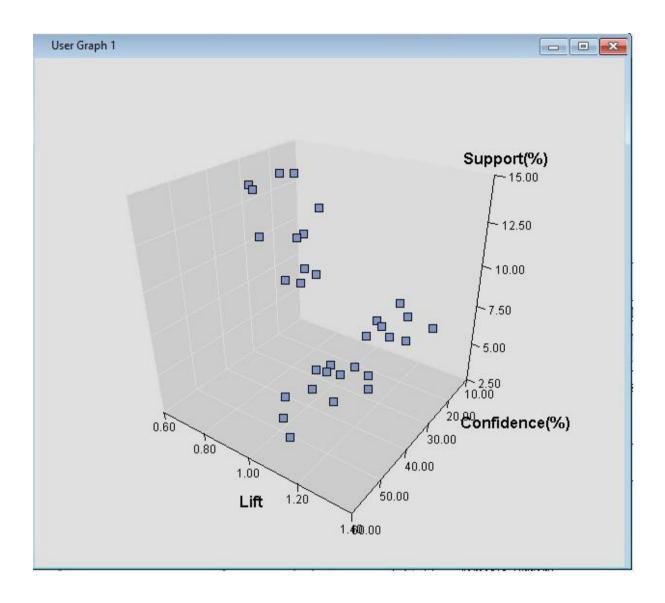








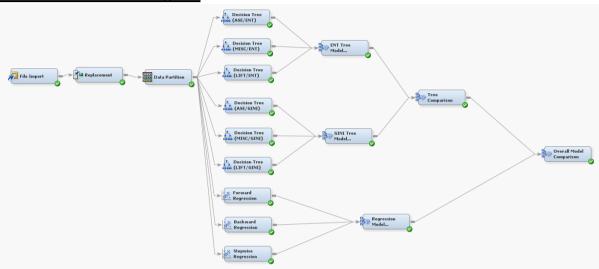
			- 1	Jse default assig	nments
▲ Variable	Role	Туре	Description	Format	
CONF	Λ	númeric	Connidence(%)	6.2	
COUNT		Numeric	Transaction Count	6.2	
EXP_CONF	i i	Numeric	Expected Confidenc	6.2	:
index		Numeric	Rule Index	1	
ПЕМ1	*	Character	Rule Item 1	100	:1
ITEM2		Character	Rule Item 2		:1
ПЕМЗ		Character	Rule Item 3	100	:1
ITEM4		Character	Rule Item 4	100	:
ITEM5	4	Character	Rule Item 5		:1
LIFT	Y	Numeric	Lift	6.2	:
RULE		Character	Rule		:
SET_SIZE		Numeric	Relations	6.	:
SUPPORT	Z	Numeric	Support(%)	6.2	:1
Transpose		Numeric	Transpose Rule	- 0:	



## Objective 5: To determine what factor influences customer's satisfaction.

Customer's satisfaction directly impacts customer loyalty and repeat purchase. It helps companies understand how well they are meeting customer's expectations and identify areas of improvement. By analyzing customer satisfaction level, companies can make strategic decisions to enhance their product and service. Finally, increase the profitability.

## **Overview of the EM diagram**



## **Data Preparation**

## 1. Replacment

Columns: L	abel	Mining	Basic		Statistics
Name	Use	Limit Method	Replacement Lower Limit	Replacement Upper Limit	Replace Method
Days_to_Ship_A	Default	Default			Default
Days_to_Ship_S	Default	Default			Default
Discount	Default	Default			Default
Number_of_Rec	Default	Default			Default
Postal_Code	Default	Default			Default
Profit	Default	Default			Default
Profit_Ratio	Default	Default			Default
Profit_per_Orde	Default	Default			Default
Quantity	Default	Default			Default
Sales	Default	User Specified	1		Default
Sales_Forecast	Default	Default			Default
Sales_per_Custo	Default	Default			Default

<sup>-</sup>prevent missing value

## 2.Data Partition

The validation dataset will be occupied 50%, and the training dataset will be occupied 50%.

General	
Node ID	Part
Imported Data	
Exported Data	
Notes	
Train	
Variables	
Output Type	Data
Partitioning Method	Default
Random Seed	12345
Data Set Allocations	
-Training	50.0
-Validation	50.0
-Test	0.0
Report	
Interval Targets	Yes
Class Targets	Yes

## **Methodology**

We will split the data into a (50%) training set and a (50%) testing set.

The target variable: **Satisfaction** 

The Input variables {Ship Status, Discount, Category, Sales per Customer}

Name	Role 🛆	Level	Report	Order	Drop	Lower Limit	Upper Limit
Order_ID	ID	Nominal	No		No		
Discount	Input	Interval	No		No		
Ship_Status	Input	Nominal	No		No		
Sales_per_Cust	Input	Interval	No		No		
Category	Input	Nominal	No		No		
Region	Rejected	Nominal	No		No		
Sales	Rejected	Interval	No		No		
Profit_per_Orde	Rejected	Interval	No		No		
Quantity	Rejected	Interval	No		No		
Ship_Date	Rejected	Nominal	No		No		
State	Rejected	Nominal	No		No		
Ship_Mode	Rejected	Nominal	No		No		
Sales_Forecast	Rejected	Interval	No		No		
Sub_Category	Rejected	Nominal	No		No		
City	Rejected	Nominal	No		No		
Days_to_Ship_S	Rejected	Interval	No		No		
Number_of_Rec	Rejected	Interval	No		No		
Customer_Name	Rejected	Nominal	No		No		
Country	Rejected	Nominal	No		No		
Days_to_Ship_A	Rejected	Interval	No		No		
Profit	Rejected	Interval	No		No		
Product_Name	Rejected	Nominal	No		No		
Profit_Ratio	Rejected	Interval	No		No		
Order_Date	Rejected	Nominal	No		No		
Postal_Code	Rejected	Interval	No		No		
Segment	Segment	Nominal	No		No		
Satisfaction	Target	Ordinal	No		No		

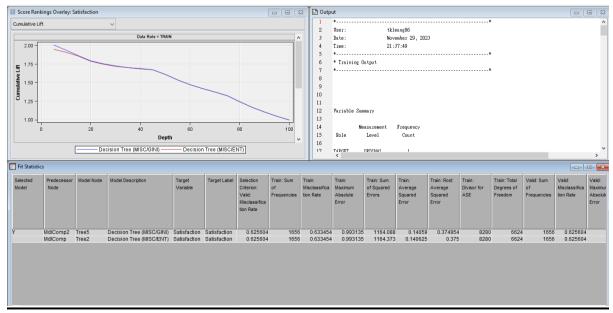
#### 1. Decision Tree

We will use those input variables to build 2 tree to determine those variable importance towards satisfaction. Then, We will use those splitting criterion (Entropy, and Gini) for a decision tree as impurity measures to evaluate a split at each node. Besides, (misclassification, Average Square Error and Lift) is the assessment measure.

			Property	Value	
General			Number of Rules	5	^
Node ID	Tree		Number of Surrogate Rules	0	
Imported Data			Split Size		
Exported Data			Split Search		
Notes			Use Decisions	No	
Train			Use Priors	No	
Variables			Exhaustive	5000	
Interactive			Node Sample	20000	
Import Tree Model	No		Subtree		
Tree Model Data Set			Method	Assessment	
Use Frozen Tree	No		Number of Leaves	1	
Use Multiple Targets	No		Assessment Measure	Average Square Error 🔍	/
Splitting Rule			Assessment Fraction	0.25	
Interval Target Criterion	ProbF		Cross Validation		
Nominal Target Criterion	ProbChisq		Perform Cross Validation	No	
Ordinal Target Criterion	Entropy	~	Number of Subsets	10	
Significance Level	0.2		Number of Repeats	1	
Missing Values	Use in search		Seed	12345	
Use Input Once	No		Observation Based Importa		
Maximum Branch	2		Observation Based Importa	No	~
					_

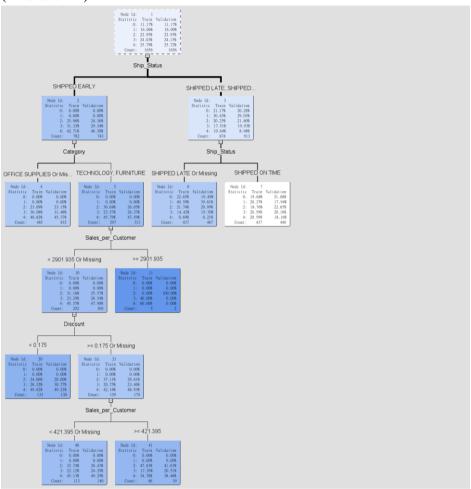
#### **Tree Model Comparison**

Initially, we tested two different nominal splitting rules (Entropy, and Gini) for a decision tree with a maximum of two splits, and the Both Entropy and Gini yielded the best results; subsequently, (MISC/GINI)(MISC/ENT) exhibited the lowest validation misclassification rate. Additionally, applying the decision tree after imputation improves the prediction in this instance. Below are the context and results of this decision tree:



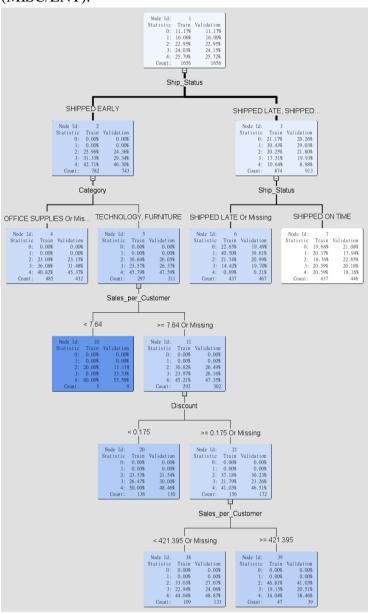
## **Results:**

# (MISC/GINI):



70						
71						Ratio of
72			Number of			Validation
73			Splitting		Validation	to Training
74	Variable Name	Label	Rules	Importance	Importance	Importance
75						
76	Ship_Status		2	1.0000	1.0000	1.0000
77	Category	Category	1	0.1858	0.0000	0.0000
78	Sales_per_Customer		2	0.1217	0.1078	0.8854
79	Discount	Discount	1	0.1210	0.0679	0.5608
80						

## (MISC/ENT):



70						
71						Ratio of
72			Number of			Validation
73			Splitting		Validation	to Training
74	Variable Name	Label	Rules	Importance	Importance	Importance
75						
76	Ship_Status		2	1.0000	1.0000	1.0000
77	Category	Category	1	0.1858	0.0000	0.0000
78	Discount	Discount	1	0.1285	0.0341	0.2651
79	Sales_per_Customer		2	0.1233	0.1025	0.8311
80						

#### **Logistic Regression**

We will use Logistic Regression to iteratively remove independent variables which are not important to the target variable from a model to simplify it and improve its interpretability and predictive performance. The resulting model will only include the predictors that are statistically significant and contribute meaningfully to the predict the target variable(satisfaction). It has 3 selection methods, which are forward, backward, and stepwise.

Selection Options		;
. Property	Value	
Sequential Order	No	
Entry Significance Level	1.0	
Stay Significance Level	0.5	
Start Variable Number	0	
Stop Variable Number	0	
Force Candidate Effects	0	
Hierarchy Effects	Class	
Moving Effect Rule	None	
Maximum Number of Steps	20	

#### **Results:**

Those 3 selection modeling are the same misclassification in these three models.

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Misclassifica tion Rate
	Reg		Forward Re		Satisfaction	0.619565
	Reg3	Reg3	Stepwise R	Satisfaction	Satisfaction	0.619565
	Reg2	Reg2	Backward	Satisfaction	Satisfaction	0.619565

	Analysis of Maximum Likelihood Estimates								
				Standard	Wald		Standardized		
Parameter		DF	Estimate	Error	Chi-Square	Pr > ChiSq	Estimate	Exp(Est)	
Intercept	4	1	-1.0572	0.0562	354.17	<.0001		0.347	
Intercept	3	1	-0.00725	0.0491	0.02	0.8828		0.993	
Intercept	2	1	0.9828	0.0552	316.96	<.0001		2.672	
Intercept	1	1	2.0733	0.0780	706.42	<.0001		7.951	

## All model comparison

After comparing the Average Squared error of the two final models, which are Decision tree (Gini), Logistic regression (Forwardward). The Decision tree (MISC/GINI) performs the best, which is the lowest Average Squared error.

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Average Squared Error
Υ	MdlComp3	Tree5	Decision Tree (MISC/GINI)	Satisfaction	Satisfaction	0.141784
	MdlComp4	Reg	Forward Regression	Satisfaction	Satisfaction	0.144864