UNIVERSITI MALAYA

MASTER OF DATA SCIENCE (SEMESTER 1 – 2023/2024)

FACULTY OF COMPUTER SCIENCE & INFORMATION TECHNOLOGY

WQD 7005 Data Mining

CASE STUDY (ALTERNATIVE ASSESSMENT 1)

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Introduction

E-commerce is an ever-growing industry in modern society. Data analysis is critical in the fast-paced world of e-commerce for uncovering insights that fuel educated decision-making. The sheer volume of data created by online enterprises presents a goldmine of information begging to be studied.

In this case study, a hypothetical dataset containing the core attributes that are typically present in e-commerce dataset will be examined. The dataset will undergo pre-processing using Talend Data Integration and Talend Data Preparation. After that, the pre-processed dataset will undergo analysis using a decision tree to identify patterns. The dataset will also undergo modelling using ensemble and gradient boosting method. Both analysis and modelling will be carried out in SAS Enterprise Miner.

Dataset Description

Two hypothetical datasets are created, "customer_data.csv" and "customer_marketing.csv" where customer data refers to the personal details of the customer which includes their basic information like age, gender, location. It also contains certain relevant information that pertains to their information as a consumer, such as total spendings, membership level etc. On the other hand, the customer marketing data is curated due to a recent marketing campaign where the customers are asked to subscribe to newsletters in the form or email and phone. It also asks the customers to rate their service as of the time of the marketing campaign.

With that in mind, a brief description of both datasets is provided below.

Customer_data		
Parameters	**Type**	**Description**
CustomerID	ID	The ID of each customer
Age	Integer	Age of the customer
Gender	Character	Gender of the customer Available categories: Male, Female, Others
Location	Character	Location of the customer
MembershipLevel	Character	Membership level of the customer Available categories: Bronze, Silver, Gold, Platinum
TotalPurchase	Integer	The number of items the customer has brought so far
TotalSpent	Float	The amount of money spent on purchases by customer so far

Customer_data		
Parameters	**Type**	**Description**
FavouriteCategory	Character	Most bought category of items from customer Available categories: Books, Electronics, Sporting Goods, Home Goods, Clothing
LastPurchaseDate	Date	Most recent date that the customer brought items from shop
PreferredPaymentMethod	Character	Preferred payment method by customers Available: Paypal, DebitCard, CreditCard, Cash
Churn	Binary	Whether the customer has churned or not

Customer_marketing		
Parameters	**Type**	**Description**
CustomerID	ID	The ID of each customer
EmailSubscription	Binary	Whether the customer has subscribed to newsletter using email address
PhoneSubscription	Binary	Whether the customer has subscribed to newsletter using phone number
CustomerSatisfaction	Ordinal	Ranked from 1 to 5, with 5 being the best, the quality of service

In total, there are 11 attributes in customer data and 4 attributes in customer marketing. Both dataset have 500 observations and they can be joined using CustomerID.

Our target in this analysis is to predict whether the customer will churn or not hence our target variable is in customer data, which is “Churn”. With the introduction of new data entries from customer marketing, the two datasets present here will give us insight into what could possibly cause a customer to churn.

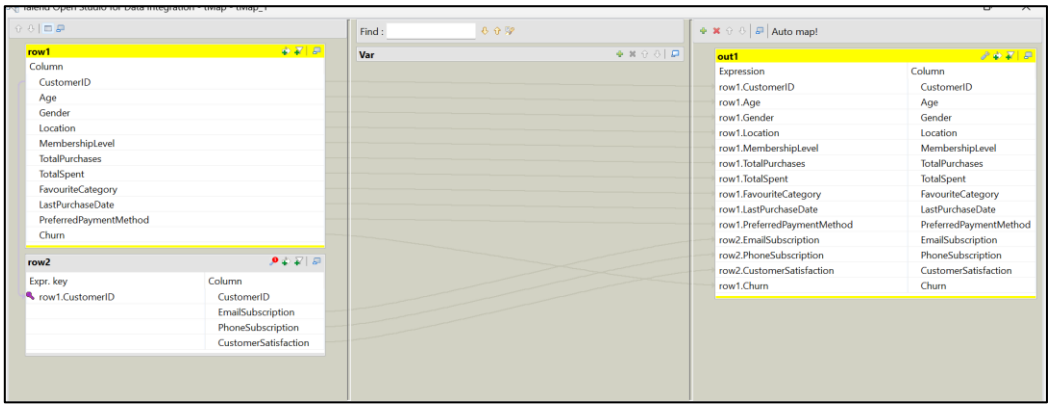
Data Pre-Processing

In this section, data preprocessing will be carried out. It is essential for the dataset to remove any potential errors that may be present in the original dataset, such as missing values, inconsistencies, and formatting errors. This process also involves combining two datasets (customer_data & customer_marketing) to generate a complete dataset for our analysis in the next few stages.

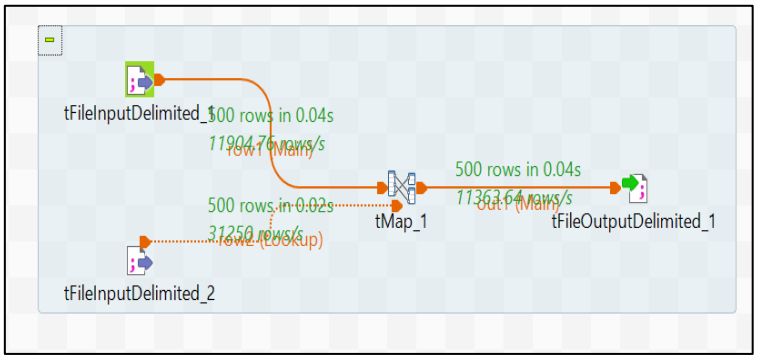
First, we combine the dataset. This is done using Talend Data Integration. Upon starting up the program, we can use the search function located at the top right of the window to look for our required functions. The functions involved are “tFileInputDelimited”, “tMap”, and “tFileOutputDelimited”.

Two “tFileInputDelimited” function is first dragged into the workspace. Both datasets are loaded into each node. The field separator is modified from “;” to “,” because the csv file is separated using comma instead of semicolon. After that, the schema is built for both datasets, which is just mapping each attribute into the schema, and the job is ready to run.

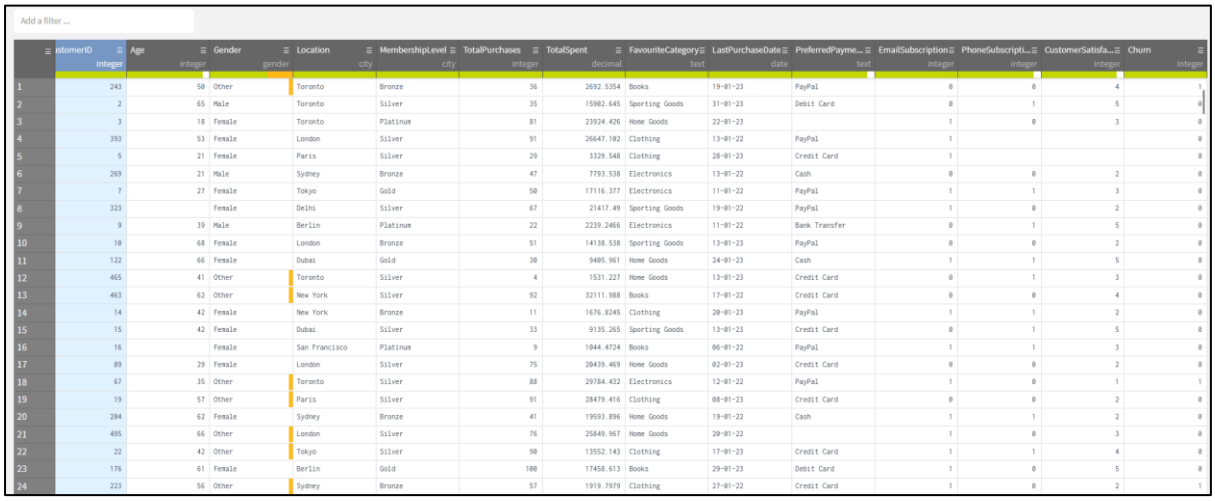
After loading the datasets into the workspace, we can combine them using the “tMap” function. Before running the job, we check the map editor and mapped the attributes that we want to combine. The desired output should be like the diagram shown below, where the individual rows of attributes from “row1” is dragged manually to “out1” located on the right side of the editor. To join both datasets, we can use “row1.CustomerID” as the key to join the attributes located in “row2”. Hence, we can add the attributes from “row2” to “out1” respectively.



After mapping the attributes, we add the last function into the workspace, which is “tFileOutputDelimited”, which allows us to generate a new csv file with the updated mapped function from “tMap”. The final workspace diagram is shown below and the new csv file is generated in the local machine

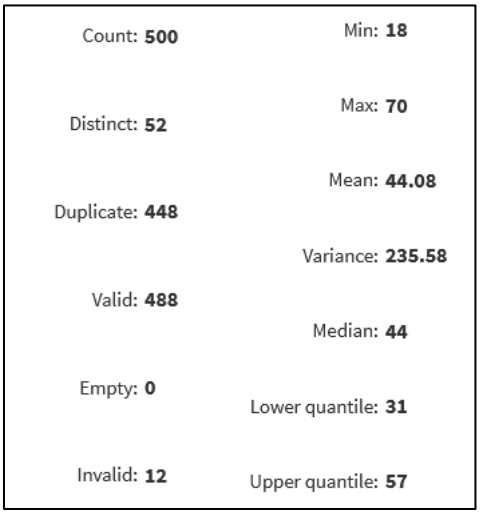


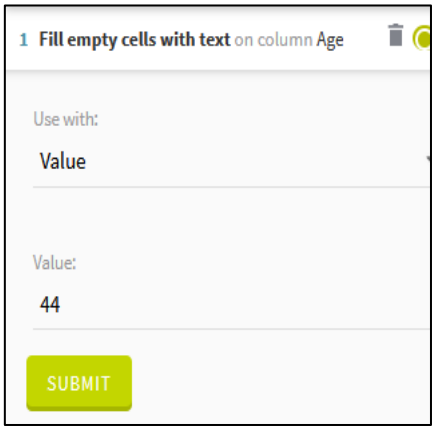
The next step of preprocessing is to check for any errors in our newly unified dataset. This can be done using Talend Data Preparation. The dataset is loaded into the workspace and an overview is constructed.



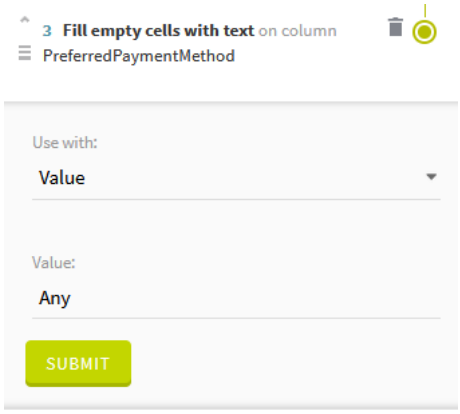
	stomerID	Age	Gender	Location	MembershipLevel	TotalPurchases	TotalSpent	FavouriteCategory	LastPurchaseDate	PreferredPayme...	EmailSubscription	PhoneSubscripti...	CustomerSatisfa...	Churn
	integer	integer	gender	city	city	integer	decimal	text	date	text	integer	integer	integer	integer
1	243	50	Other	Toronto	Bronze	36	2692.5354	Books	19-01-23	PayPal	0	0	4	1
2	2	65	Male	Toronto	Silver	35	15902.645	Sporting Goods	31-01-23	Debit Card	0	1	5	0
3	3	18	Female	Toronto	Platinum	81	23924.426	Home Goods	22-01-23		1	0	3	0
4	393	53	Female	London	Silver	91	26647.102	Clothing	13-01-22	PayPal	1			0
5	5	21	Female	Paris	Silver	29	3329.548	Clothing	28-01-23	Credit Card	1			0
6	269	21	Male	Sydney	Bronze	47	7793.538	Electronics	13-01-22	Cash	0	0	2	0
7	7	27	Female	Tokyo	Gold	50	17116.377	Electronics	11-01-22	PayPal	1	1	3	0
8	323		Female	Delhi	Silver	67	21417.49	Sporting Goods	19-01-22	PayPal	1	0	2	0
9	9	39	Male	Berlin	Platinum	22	2239.2466	Electronics	11-01-22	Bank Transfer	0	1	5	0
10	10	68	Female	London	Bronze	51	14138.538	Sporting Goods	13-01-23	PayPal	0	0	2	0
11	122	66	Female	Dubai	Gold	30	9405.961	Home Goods	24-01-23	Cash	1	1	5	0
12	465	41	Other	Toronto	Silver	4	1531.227	Home Goods	13-01-23	Credit Card	0	1	3	0
13	463	62	Other	New York	Silver	92	32111.988	Books	17-01-22	Credit Card	0	0	4	0
14	14	42	Female	New York	Bronze	11	1676.8245	Clothing	20-01-23	PayPal	1	1	2	0
15	15	42	Female	Dubai	Silver	33	9135.265	Sporting Goods	13-01-23	Credit Card	0	1	5	0
16	16		Female	San Francisco	Platinum	9	1044.4724	Books	06-01-22	PayPal	1	1	3	0
17	89	29	Female	London	Silver	75	20439.469	Home Goods	02-01-23	Credit Card	0	0	2	0
18	67	35	Other	Toronto	Silver	88	29784.432	Electronics	12-01-22	PayPal	1	0	1	1
19	19	57	Other	Paris	Silver	91	28479.416	Clothing	08-01-23	Credit Card	0	0	2	0
20	284	62	Female	Sydney	Bronze	41	19593.896	Home Goods	19-01-22	Cash	1	1	2	0
21	495	66	Other	London	Silver	76	25849.967	Home Goods	20-01-22		1	0	3	0
22	22	42	Other	Tokyo	Silver	90	13552.143	Clothing	17-01-23	Credit Card	1	1	4	0
23	176	61	Female	Berlin	Gold	100	17458.613	Books	29-01-23	Debit Card	1	0	5	0
24	223	56	Other	Sydney	Bronze	57	1919.7979	Clothing	27-01-22	Credit Card	1	0	2	1

It is observed that there are a few missing values located in some observations, particularly in Age, PreferredPaymentMethod, PhoneSubscription, and CustomerSatisfaction. For numerical variables like Age, we can impute the missing values with its median, that way we can safely inject new values into the column without skewing the existing distribution of the variable. Upon inspection, there are a total of 12 missing values in Age, hence all 12 of them is imputed with the median value of 44. The “Gender” errors are neglected because some countries do have “Others” as an option in the Gender information.





For PreferredPaymentMethod, there are a few missing values present in the variable, however it is categorical in nature and we can’t impute through mathematical means. We can use the mode however the distribution may be skewed as the dataset is not big enough for the mode imputation to be negligible. Hence, a new level is introduced. If there are missing values in PreferredPaymentMethod, we just impute it with “Any”, which means that the customer have no preference and are good with just any type of payment method.

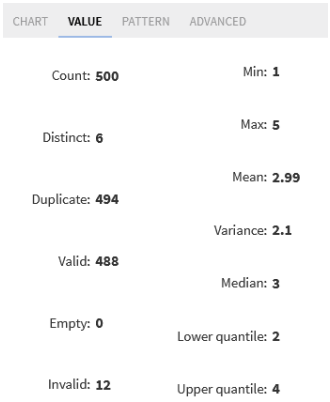


Debit Card
PayPal
Credit Card
Cash

Debit Card
Any
PayPal
Credit Card

Next up is the missing values that was carried forward from the customer_marketing dataset, which is PhoneSubscription and CustomerSatisfaction. Since we have the dataset now, the marketing campaign has most likely ended and we can't follow up with the customer anymore. Hence, we can assume that the missing values in PhoneSubscription can be imputed as 0, meaning that they didn't subscribe to newsletters with phone number.

As for the CustomerSatisfaction, the variable is ranked in an ordinal scale, with 5 being the best and 1 being the worst. The median will be used to impute missing values for the satisfactory score because it does not skew the distribution. The value of median is 3, which is the average customer experience.

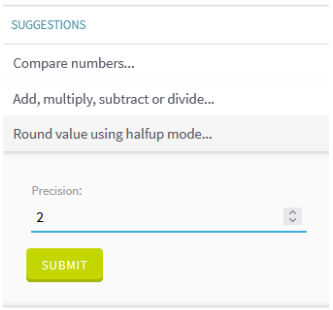


PhoneSubscripti... integer	CustomerSatisfa... integer
0	4
1	5
0	3
0	2
1	3
0	2

PhoneSubscripti... integer	CustomerSatisfa... integer
1	5
1	5
0	3
1	3
0	3
1	3
1	3
1	3
1	5

We also noticed that when PhoneSubscription is missing, the CustomerSatisfaction will also be missing. This is most likely because the marketing campaign is carried out remotely and the information for CustomerSatisfaction is generated using an application. Hence both missing values just means that the customer either does not have a smartphone or has not downloaded the app.

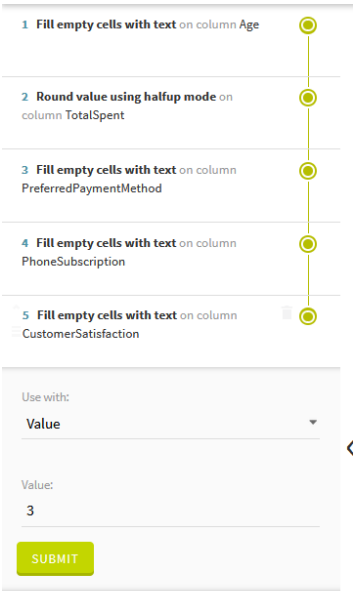
Finally, we reduce the number of decimal points located in TotalSpent, this is to ensure consistencies with the format of currency that typically contains just 2 decimal points. We can do this using the round value function and choose 2 precision points.



	TotalSpent decimal	FavoriteCatego
36	2692.5353	Books
35	15902.6443	Sporting Goods
31	23924.4261	Home Goods
31	26647.1017	Clothing
29	3329.5481	Clothing
47	7793.5383	Electronics
50	17116.3774	Electronics
57	21417.4898	Sporting Goods

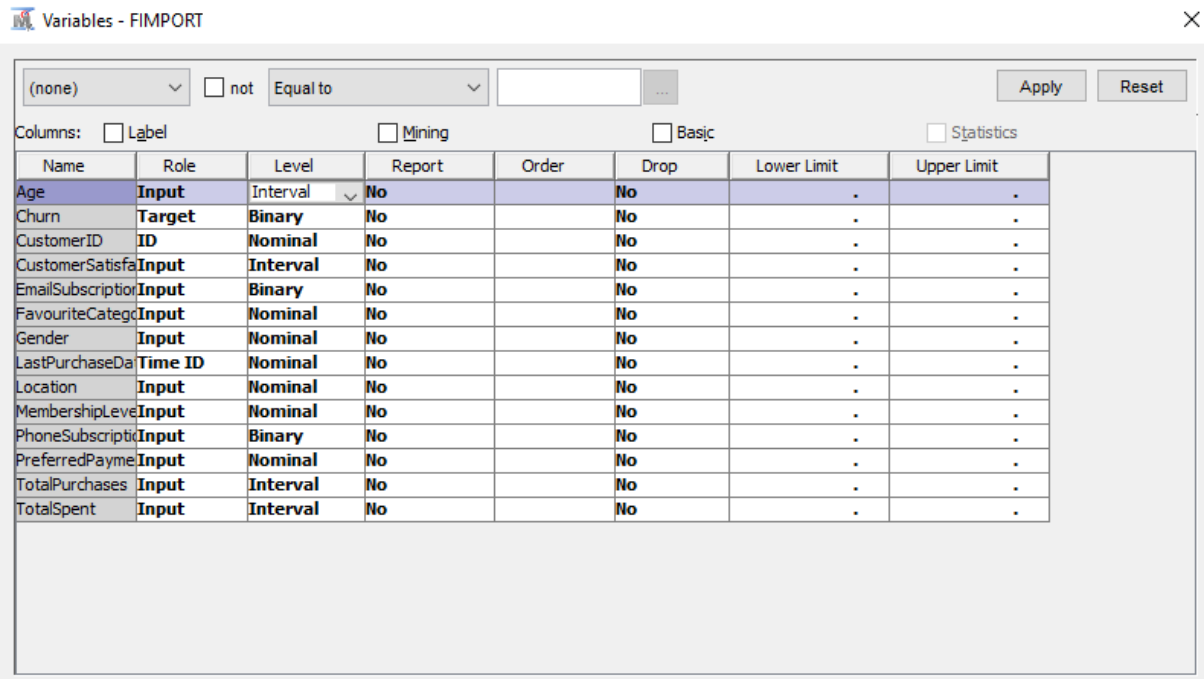
TotalSpent decimal	FavoriteCategory text
2692.54	Books
15902.64	Sporting Goods
23924.43	Home Goods
26647.10	Clothing
3329.55	Clothing
7793.54	Electronics
17116.38	Electronics
21417.49	Sporting Goods
2239.25	Electronics

With that, we conclude our preprocessing phase of the case study. The final workflow in Talend Data Preparation is shown below. Basically, we have just made adjustments to impute missing values without the need of removing said observations, we also performed some adjustments in making sure the format is standardized such as the currency format. The final dataset is generated and will be ready for the next phase of the case study.



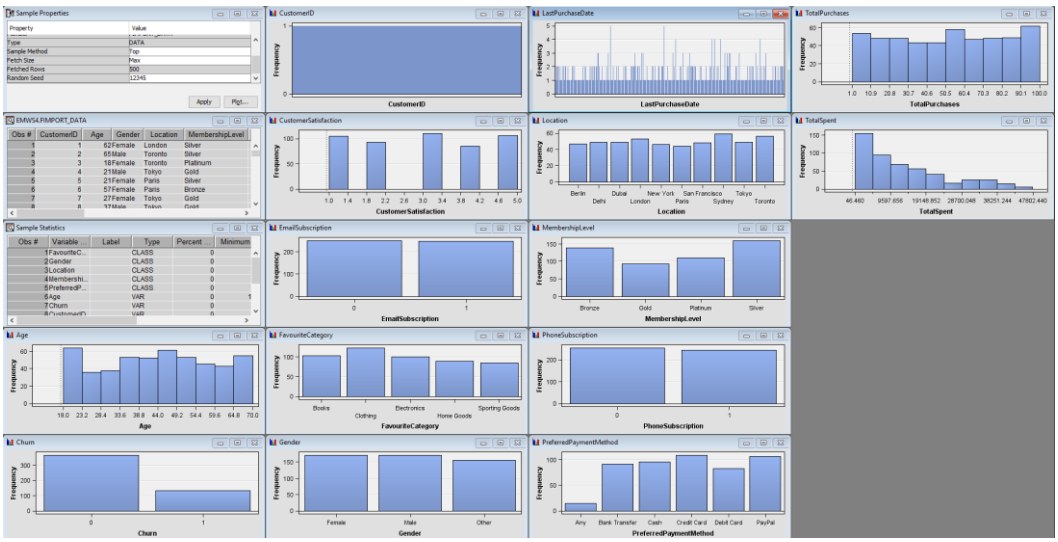
Importing Dataset into SAS

The cleaned dataset is then imported into SAS Enterprise Miner using the File Import node. The variables are then examined using the "Edit Variables" option. It is found that we have to set "Churn" as our target variable and designate "CustomerID" as ID so that it won't consider as an input in our modelling later on. The LastPurchaseDate was set to TimeID too because it contains dates. It is also observed that some variables have wrong levels such as PhoneSubscription, EmailSubscription, and Churn. Hence these 3 variables are set to "Binary" level because the attributes only have 0 and 1 as observations. The updated version will look like this.



Name	Role	Level	Report	Order	Drop	Lower Limit	Upper Limit
Age	Input	Interval	No		No	.	.
Churn	Target	Binary	No		No	.	.
CustomerID	ID	Nominal	No		No	.	.
CustomerSatisfa	Input	Interval	No		No	.	.
EmailSubscriptior	Input	Binary	No		No	.	.
FavouriteCatego	Input	Nominal	No		No	.	.
Gender	Input	Nominal	No		No	.	.
LastPurchaseDa	Time ID	Nominal	No		No	.	.
Location	Input	Nominal	No		No	.	.
MembershipLeve	Input	Nominal	No		No	.	.
PhoneSubscriptic	Input	Binary	No		No	.	.
PreferredPayme	Input	Nominal	No		No	.	.
TotalPurchases	Input	Interval	No		No	.	.
TotalSpent	Input	Interval	No		No	.	.

We performed simple exploration in our dataset to visualize the distribution of each attribute in our dataset and found that most of them are fairly distributed across all the available categories and observations. The only probable issue was the imbalance found in the "Churn" variable.

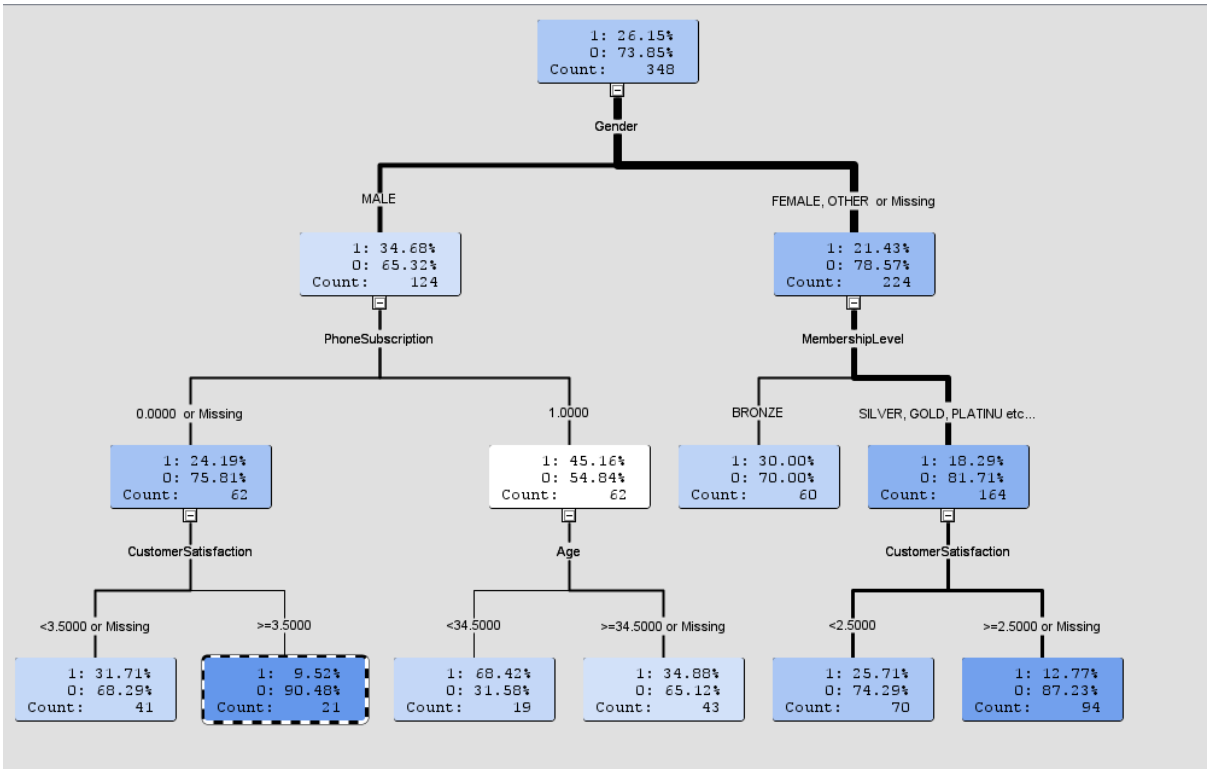


After that, we add the Data Partition Node into the workspace. This is to split the dataset into train, validate and test dataset. In this case study, we only use the train and validate dataset, hence the splitting ratio will be set to 70:30 respectively, and it is ready for modelling.

Train	
Variables	...
Output Type	Data
Partitioning Method	Default
Random Seed	12345
Data Set Allocations	
Training	70.0
Validation	30.0
Test	0.0

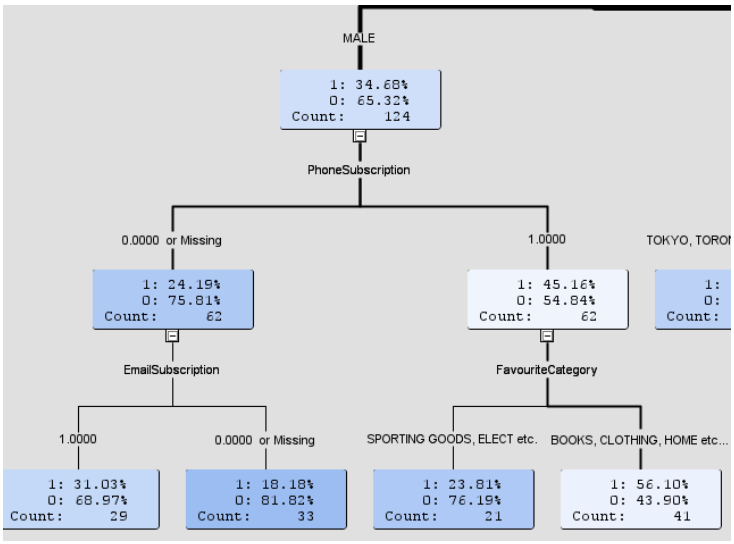
Decision Tree Analysis

First, a decision tree node was used to analyse churn behaviour of customers. After running the node, the tree map is visualized using an interactive decision tree. The tree is splitted slowly according to which variable that gives the most information gain when splitting. The optimally splitted map is shown below.

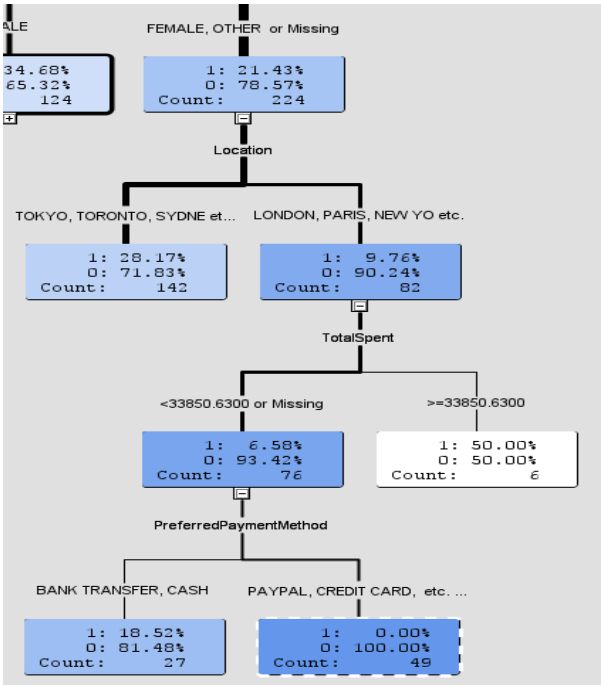


In general, the main demographic who don't churn mainly consists of female shoppers who holds a silver or above membership level. In their most recent marketing campaign, these group of female shoppers most likely left a positive review and will be most likely to continue shopping at said establishments. As for the males, it depends whether they subscribed to newsletter with their phone numbers or not, if they don't, generally they will give a more positive customer satisfactory score and retain as a customer.

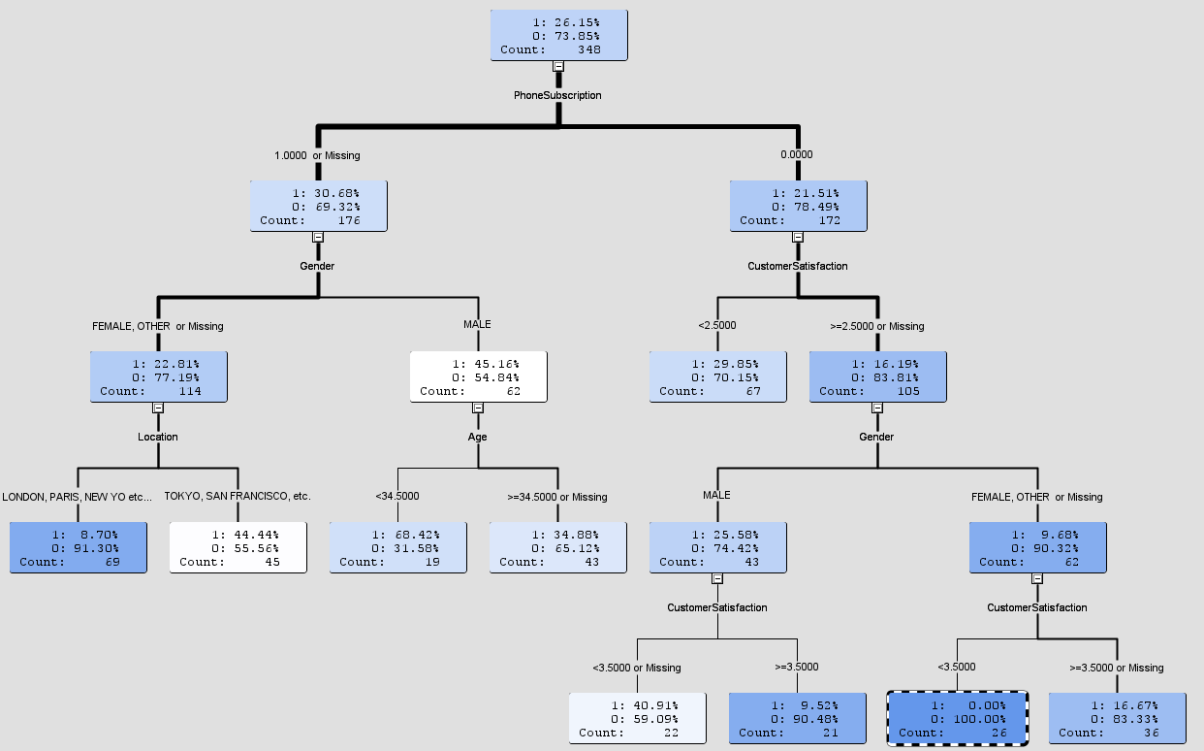
If we pruned the branches after male branch and split them using the variable with 2nd highest information gain, which is “EmailSubscription” and “FavouriteCategory”, it is observed that male shoppers who don’t subscribe to newsletters with phone will not likely be subscribed using their emails too. It is also found that those who do subscribe to newsletter with their phones, tend to be interested in products like books, clothes, and home goods. However, there are also a handful of them interested in sporting goods and electronics too.



Similarly, if we pruned the branches for the females and replace it with the variable with 2nd highest information gain, it is evident that generally European female shoppers don’t churn as much as other female shoppers do in other regions. Most female shoppers in the European spend no more than 34 thousand dollars in purchases, which is the average consumption per customer due to the average income of the continent. Among those who have spent less than 34 thousand dollars so far and didn’t churn, their preferred method is usually cashless, which is PayPal and credit cards.



If we were to start back from the root and change the "Gender" splitting criteria to "PhoneSubscription", which is the 2nd highest worth in information gain, the new treemap will look something like this.



It is inferred that those who subscribe using their phones are generally female shoppers located in European locations such as London, Paris etc. And for the males, it only gives insights about their age since most male subscribers are aged 34 above.

On the other hand, for shoppers who didn't subscribe to newsletter with their phones has an above average customer satisfactory score, with female shoppers being the one who contributes most to that score, however those who don't churn will give a score in between of 2.5 and 3.5, despite having high satisfactory score, some female shoppers end up churning. For the men, the pattern is obvious as the higher score they give, the more likely they will stay, or else they will churn, even when they gave a score which is deemed "above average".

With the usage of the interactive decision tree map, not only we are able to mind insights from the tree map, but it also enables us to determine the number of branches and leaves that are suitable for the decision tree model for the most optimal results. Hence, in our decision tree model building, we set the maximum branch that the tree model could split into 2, and the depth is set to 4.

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	2
Maximum Depth	4
Minimum Categorical Size	5

Another decision tree model is constructed, but the maximum branch is set to 3 to provide a more complex algorithm that can capture extra nuances within the data. The average square error for both tree models is shown below.

Fit Statistics

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test
Churn		_NOBS_	Sum of Frequencies	348	.	152
Churn		_MISC_	Misclassification Rate	0.261494	.	0.269737
Churn		_MAX_	Maximum Absolute Err...	0.785714	.	0.785714
Churn		_SSE_	Sum of Squared Errors	128.8802	.	61.95581
Churn		_ASE_	Average Squared Error	0.185173	.	0.203802
Churn		_RASE_	Root Average Squared...	0.430317	.	0.451444
Churn		_DIV_	Divisor for ASE	696	.	304
Churn		_DFT_	Total Degrees of Free...	348	.	.

Fit Statistics

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test
Churn		_NOBS_	Sum of Frequencies	348	.	152
Churn		_MISC_	Misclassification Rate	0.247126	.	0.302632
Churn		_MAX_	Maximum Absolute Err...	0.934211	.	0.934211
Churn		_SSE_	Sum of Squared Errors	117.6788	.	67.51979
Churn		_ASE_	Average Squared Error	0.169079	.	0.222105
Churn		_RASE_	Root Average Squared...	0.411192	.	0.47128
Churn		_DIV_	Divisor for ASE	696	.	304
Churn		_DFT_	Total Degrees of Free...	348	.	.

Both models' performance is adequate to predict churn rate of customers. However, the tree models can smoothen out with the use of bagging and boosting method, which will be explored in the next section.

Gradient Boosting & Random Forest

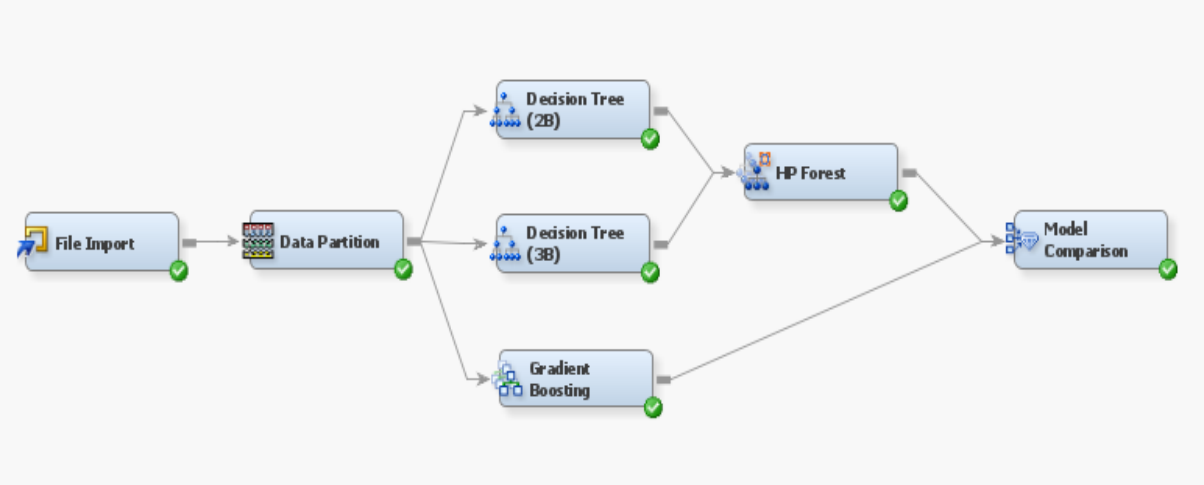
The Gradient Boosting node is then added to the workspace, and the model's depth parameter is increased to 4, resulting in a more complex network of weak learners than the default depth of 2. This change is intended to capture subtle patterns in the data and improve the model's forecasting skills for the specific characteristics of the problem at hand.

Splitting Rule	
Huber M-Regression	No
Maximum Branch	2
Maximum Depth	4
Minimum Categorical Size	5
Reuse Variable	1
Categorical Bins	30
Interval Bins	100

As a result, when paired with the ensemble technique, the two trees contribute to the model's decision-making process by utilizing their diverse views to create more accurate predictions. The random forest technique allows for a bagging technique for the decision tree models.

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	4
Minimum Categorical Size	5

The final workflow diagram looks something like this, with the included "Model Comparison" node added later during model assessment.



Model Comparison

In this stage, the models constructed are compared with each other and the "Model Comparison" is used here. The results output that Gradient Boosting method performs the best with only having a misclassification rate of 0.02%, generally the lower the rate, the better. The score is followed by random forest which has a 0.26% misclassification rate, which is still acceptable.

Selected Model	Model Node	Model Description	Misclassification Rate
Y	Boost	Gradient Boosting	0.02011
	HPDMForest	HP Forest	0.26149

Not only does the bagging method have a lower score than boosting method, but it also slightly increases the misclassification rate of the decision tree models.

Hence, the recommended model for predicting churn rate of customers is by Gradient Boosting for this dataset, however more models need to be assessed when the size of dataset grows and possibly more modifications to parameters needed to be done.

Conclusion

As a conclusion, based on the decision tree analysis, several business strategies can be adopted to boost sales and prolong customer retention.

1. **Targeted Marketing Campaigns**:
   - More marketing campaigns can be targeted for female shoppers who holds a silver membership, this not only encourage existing customer retention, but also attracts potential new customers who may sign up for the membership, enticing them to achieve silver level or above to enjoy the benefits during the campaign.

2. **Implement Region-Specific Promotions**
   - Since many who don't churn resides in the European region, the company can offer region specific promotions and offers that may increases sales in populated areas within Europe, such as having a sale on winter jacket during Winter season or promote local Europe cuisines in the establishments.

3. **Cashless Payments Cashbacks**
   - With cashless payment being the preferred method of payment by most, the company can encourage more users to shop by offering cashbacks to those who shopped until a certain threshold in a single receipt. This not only encourages users to use cashless payments more, but also encourages sales.

With these methods in mind, the company is presented with several actionable options for preventing churn from customers and encouraging customer growth. The business can address certain customer groups proactively by utilizing customized marketing efforts and adapting regional considerations. The company not only retain existing consumers but also pave the road for sustainable customer growth and improved overall business performance.