UNIVERSITY OF MALAYA

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY

MASTER OF DATA SCIENCE

WQD7005 DATA MINING

Case Study

Predicting whether e-commerce customers use coupons

Matric No.	Name
22078878	Cai Jue

Selection of the Dataset

Data Source：https://www.kaggle.com/datasets/rishikumarrajvansh/marketing-insights-for-e-commerce-company/data?select=Online_Sales.csv

The Kaggle link primarily contains five datasets, which can be used for customer behavior analysis and market forecasting. According to the case study requirements, I have chosen two datasets for mapping and merging. They are the CustomersData and Online_Sales datasets.

CustomersData：

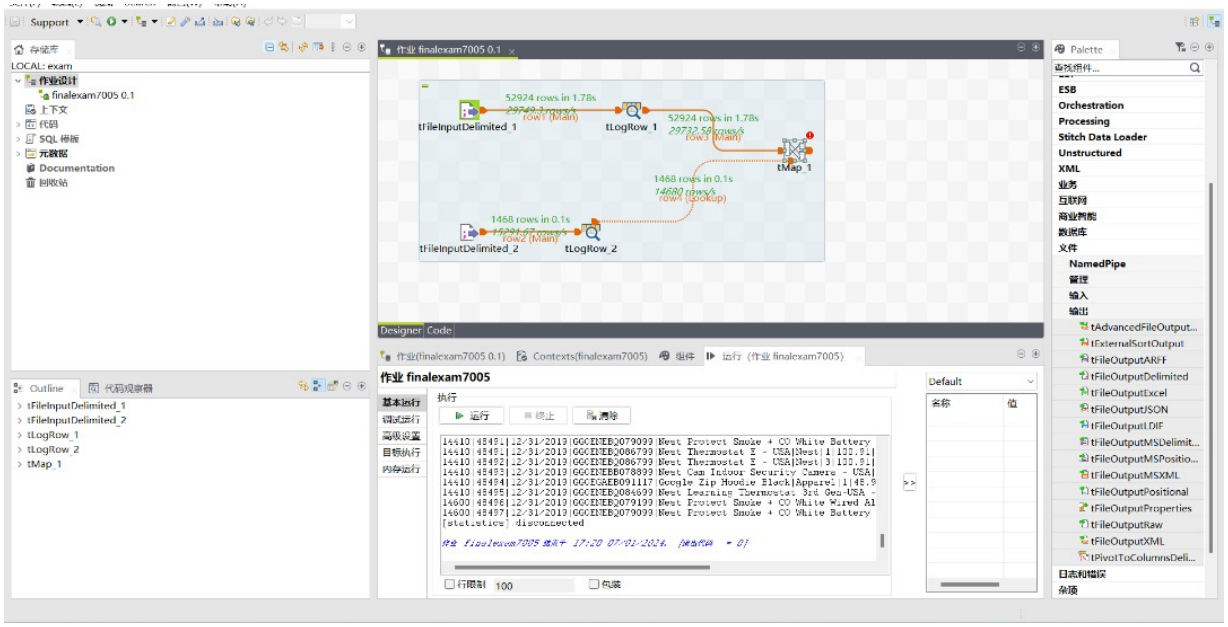
Variable	Description	Vs Dataset Structure	Decision
CustomerID	This is a unique identifier used to distinguish each customer.	CustomerID	Reserved
Gender	Customer's gender	Gender	Reserved
Location	Geographic location of the customer	Location	Reserved
Tenure_Months	The duration of the customer's account with the store, measured in months.	MembershipLevel	Reserved

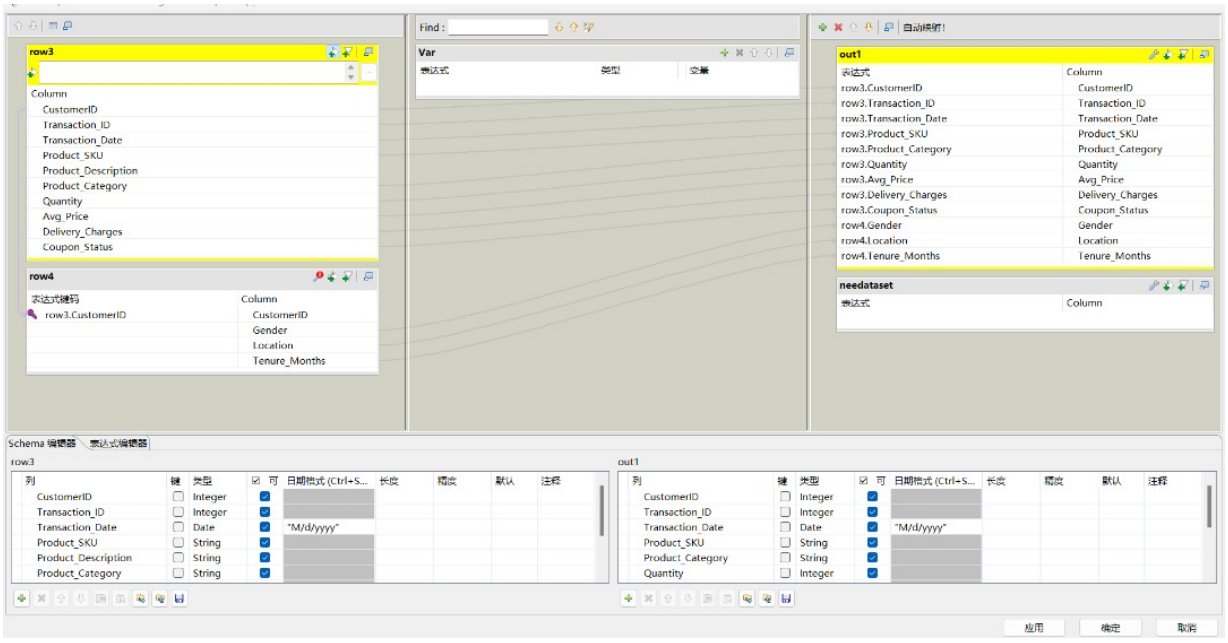
Online_Sales：

Variable	Description	Vs Dataset Structure	Decision
CustomerID	This is a unique identifier used to distinguish each customer.	CustomerID	Reserved
Transaction_ID	Customer's gender		Reserved
Transaction_Date	Geographic location of the customer	LastPurchaseDate	Reserved
Product_SKU	Transaction Unique ID		Reserved
Product_Description	Product Description		Drop
Product_Cateogry	Product Category	FavoriteCategory	Reserved
Quantity	Number of items ordered	TotalPurchases	Reserved
Avg_Price	Price per one quantity	TotalSpent	Reserved
Delivery_Charges	Charges for delivery	TotalSpent	Reserved
Coupon_Status	Any discount coupon applied	churn	Reserved

Tool 1: Use Data Integration to export the new dataset, named newdataset.

Combine the two datasets to ultimately obtain a dataset with 52,924 rows and 12 attributes for the prediction of coupon usage.

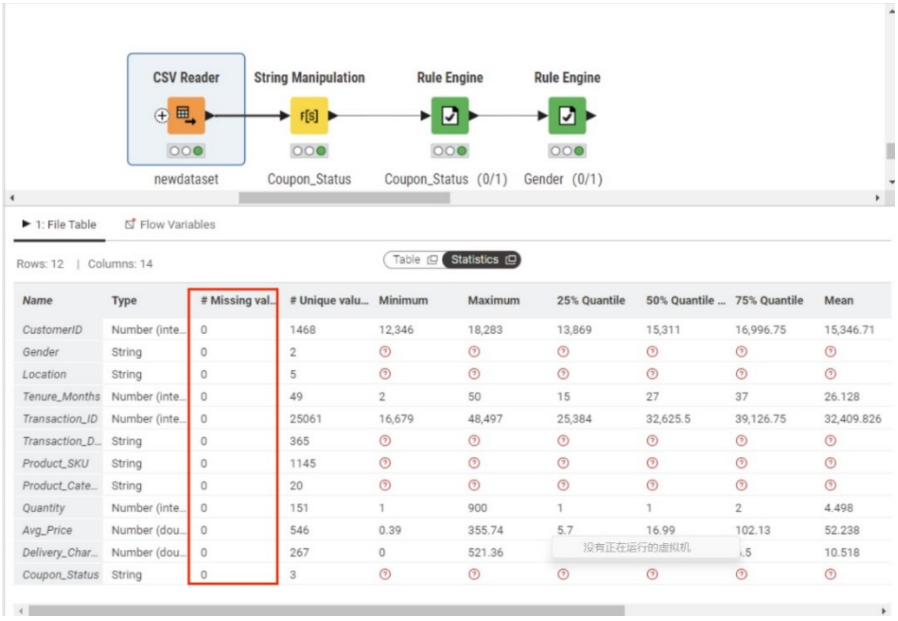




Tool 2: Use KNIME to transform and process the newdataset.

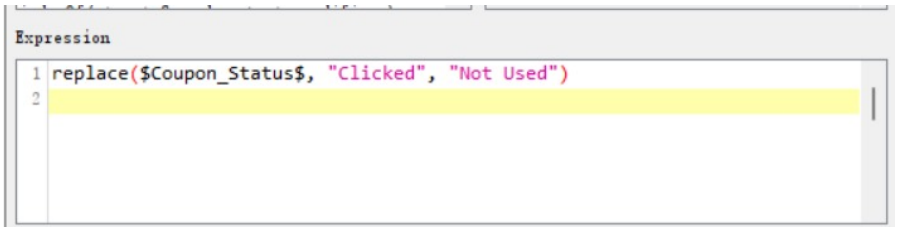
1. Check the null value situation of the newdataset.

   Null value：none

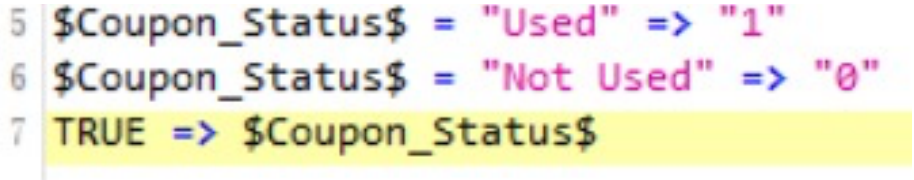


Name	Type	# Missing val...	# Unique valu...	Minimum	Maximum	25% Quantile	50% Quantile ...	75% Quantile	Mean
CustomerID	Number (inte...	0	1468	12,346	18,283	13,869	15,311	16,996.75	15,346.71
Gender	String	0	2						
Location	String	0	5						
Tenure_Months	Number (inte...	0	49	2	50	15	27	37	26.128
Transaction_ID	Number (inte...	0	25061	16,679	48,497	25,384	32,625.5	39,126.75	32,409.826
Transaction_D...	String	0	365						
Product_SKU	String	0	1145						
Product_Cate...	String	0	20						
Quantity	Number (inte...	0	151	1	900	1	1	2	4.498
Avg_Price	Number (dou...	0	546	0.39	355.74	5.7	16.99	102.13	52.238
Delivery_Char...	Number (dou...	0	267	0	521.36			.5	10.518
Coupon_Status	String	0	3						

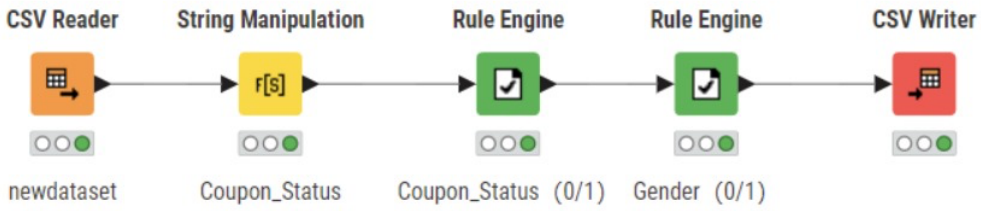
2. Convert the Coupon_Status from a ternary classification: Used, Not Used, Clicked, into a binary classification of Used and Not Used, where Clicked is considered as Not Used, in order to make the data more balanced.



3. Conduct some conversions from string to numerical values to facilitate better modeling, such as binary variables for gender and Coupon.

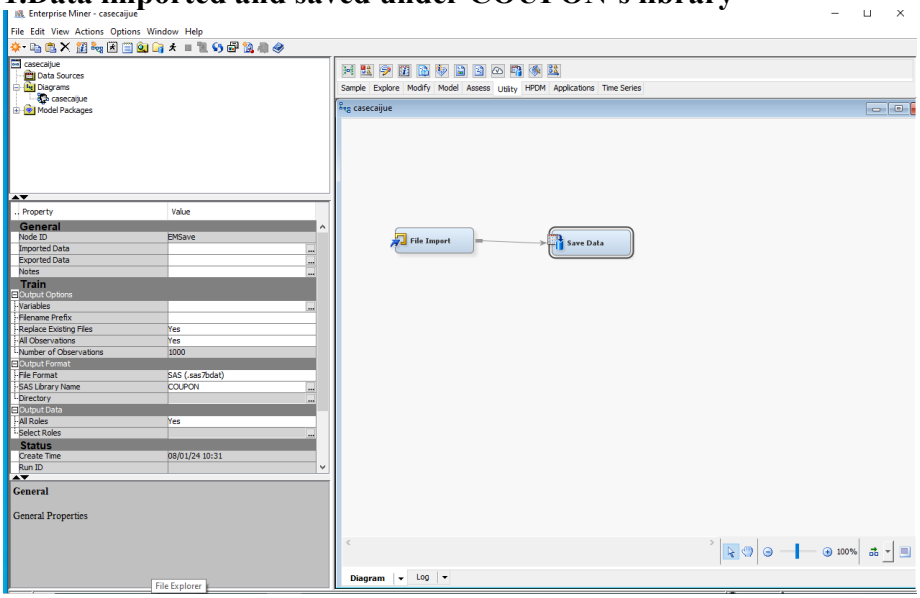


4. The overall workflow, exported as datasetfinal.csv.

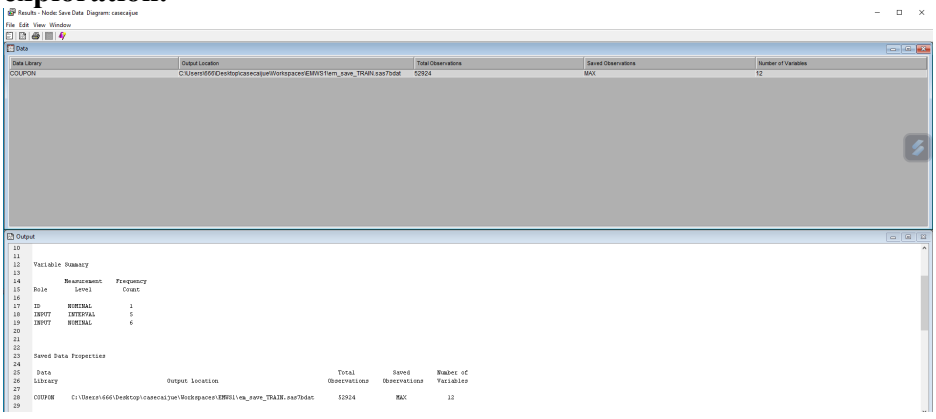


Tool3:SAS

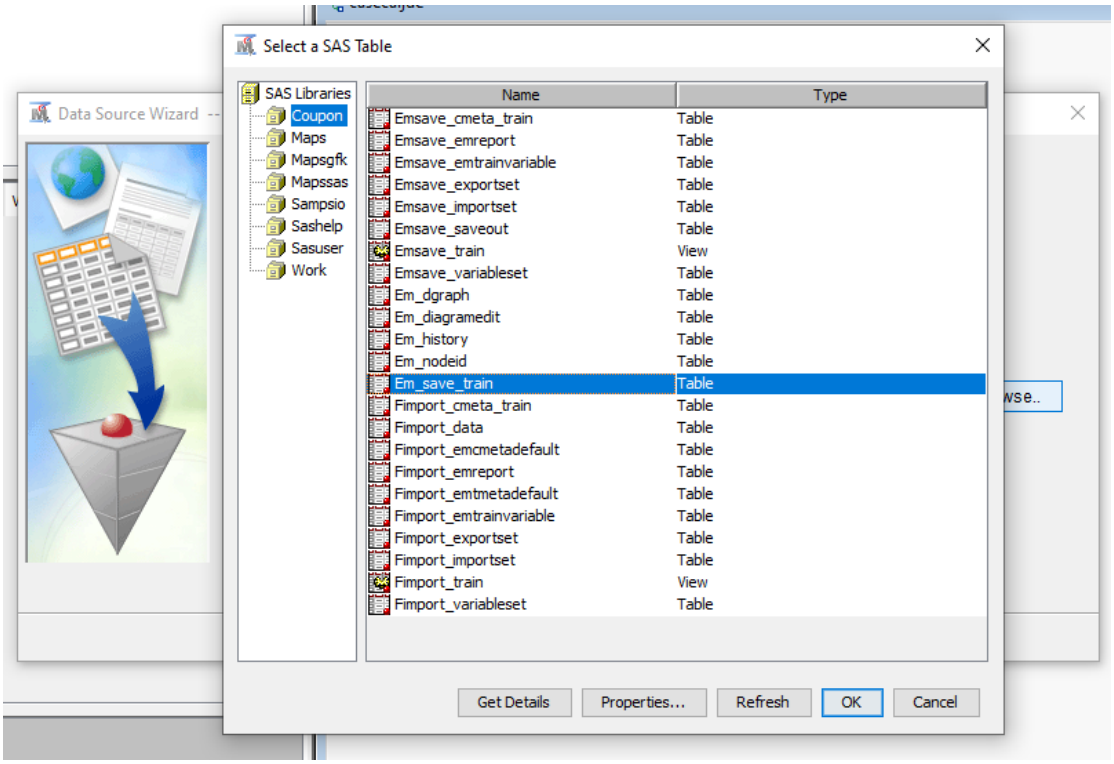
1.Data imported and saved under COUPON's library

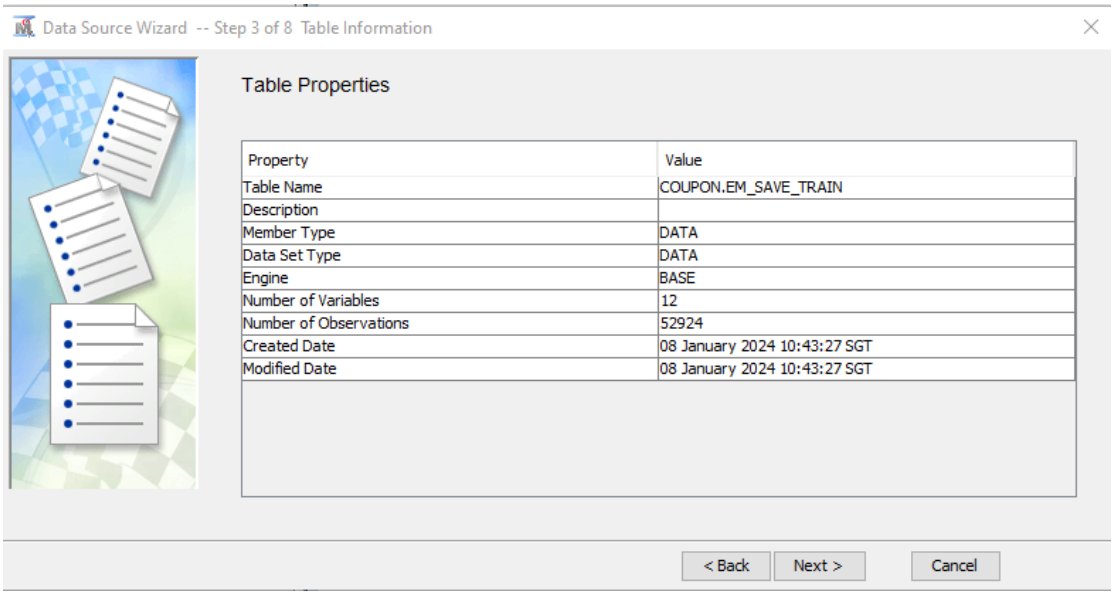


2.Check the name of the save and open this, em_save_TRAIN.sas7bat, for the next step of exploration.

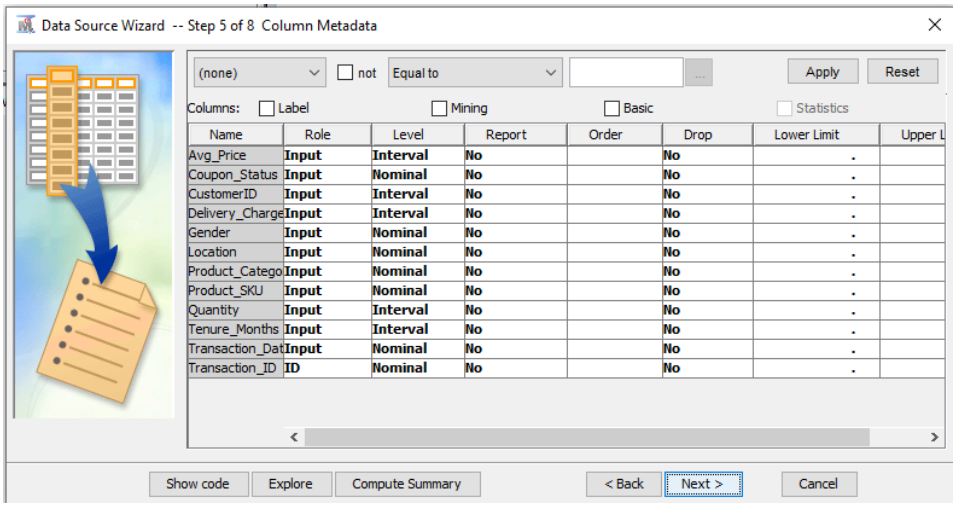


3. Select this file to explore

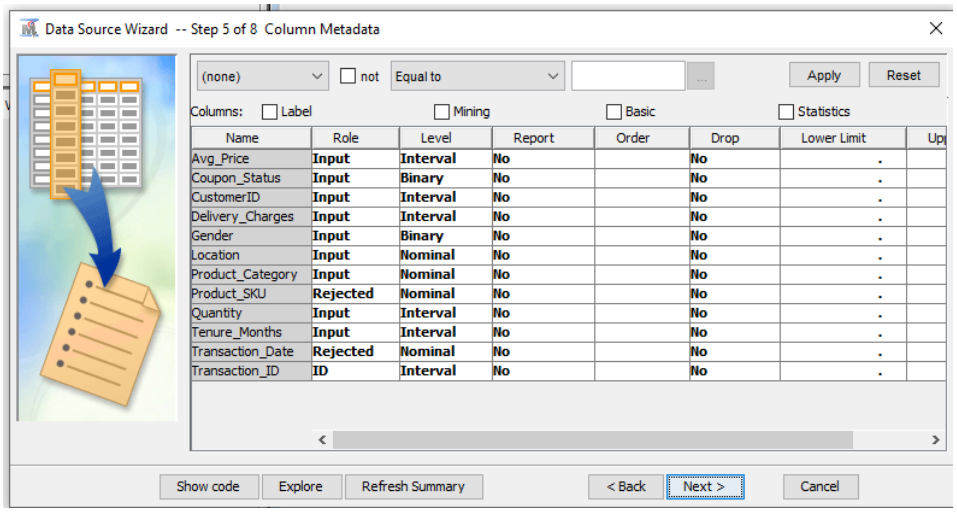




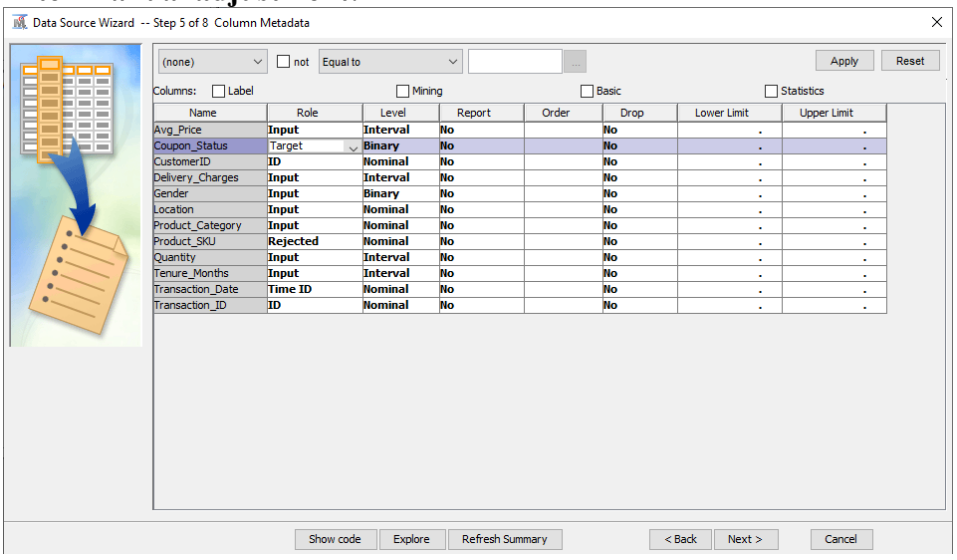
Basic Version：



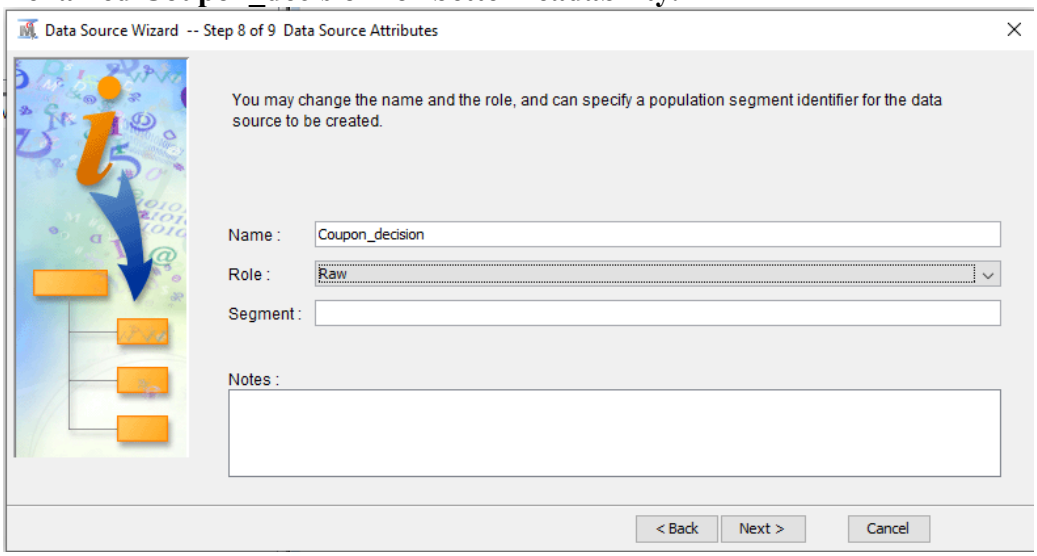
Advanced Version：



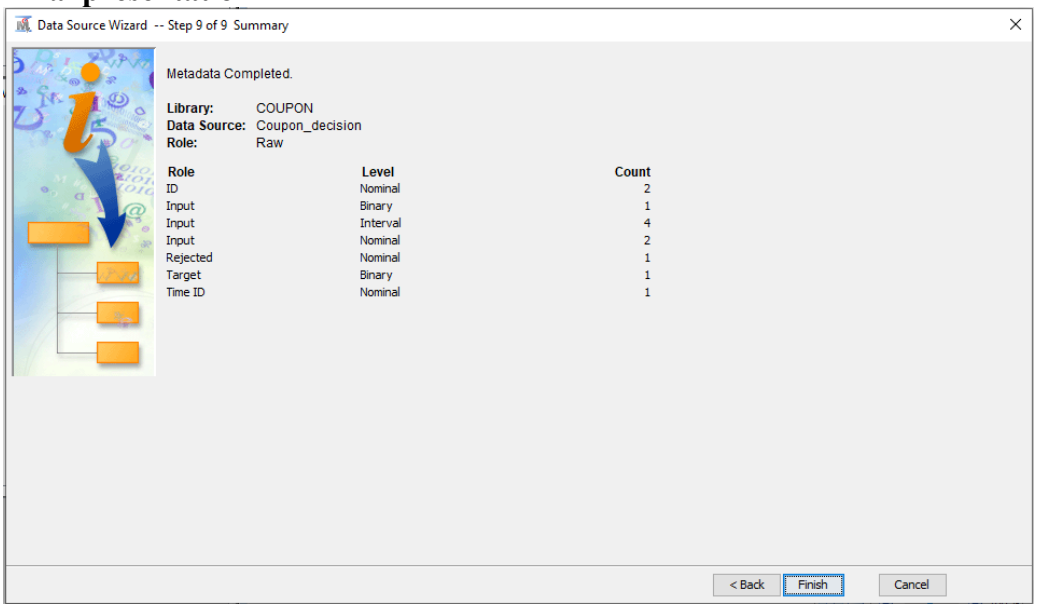
After manual adjustment:



Renamed Coupon_decision for better readability.

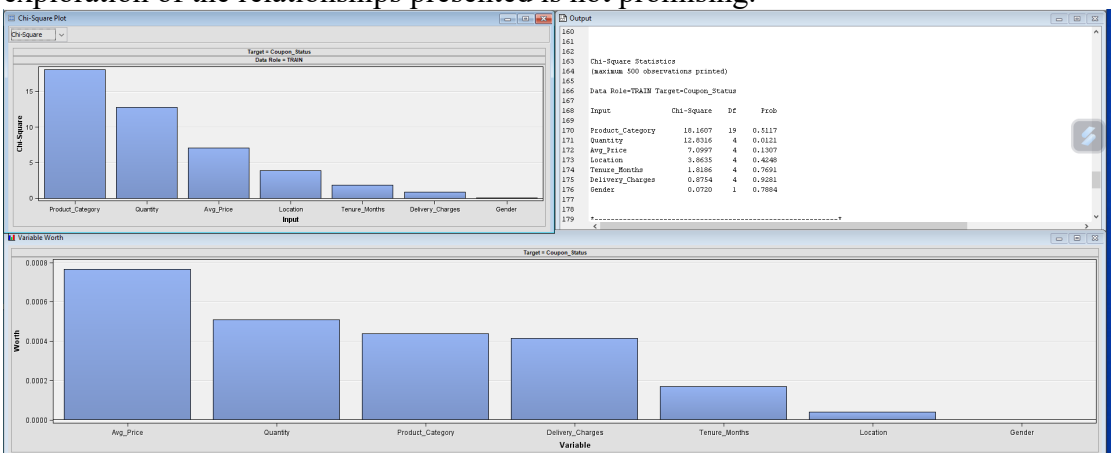


Final presentation

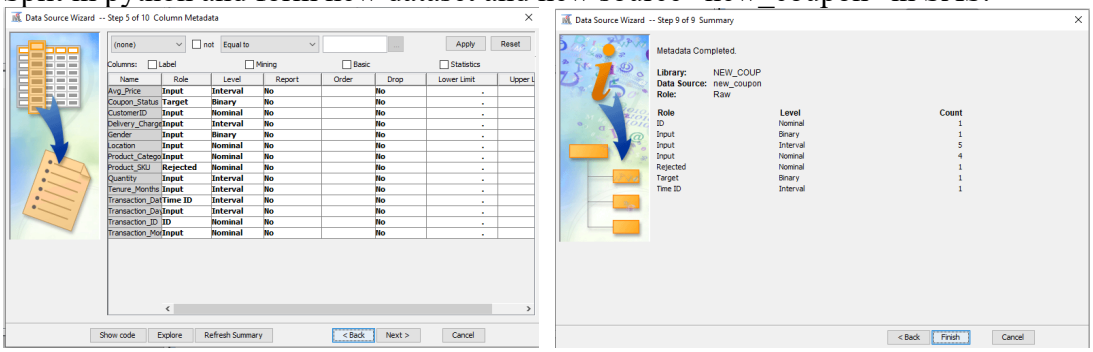


4.使用 StatExplore

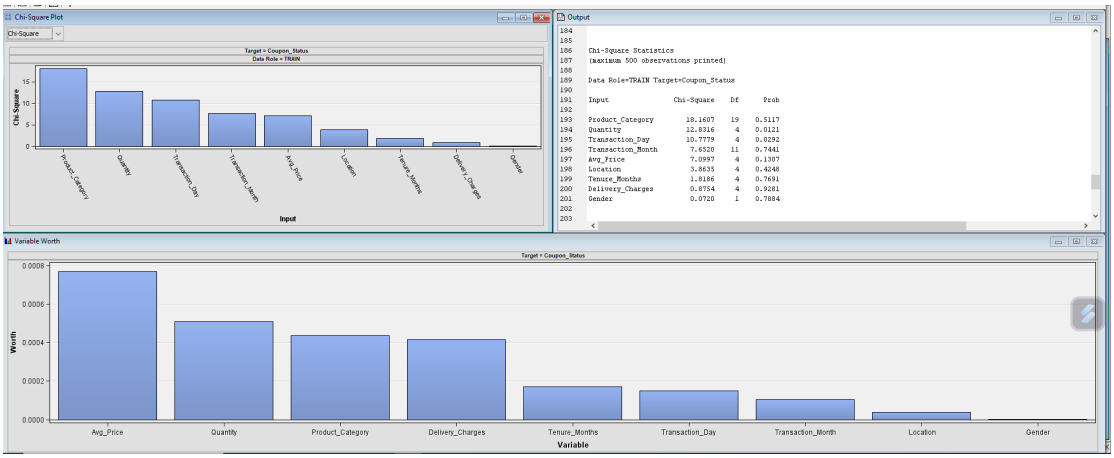
Looking at the relationship between INPUT and TARGET, since the cardinality shows no obvious relationship and only QUANTITY presents a certain relationship, I considered the possibility that the month of purchase and the day of the month might also have an effect, so I felt that from creating a new SOURCE for the comparison, splitting the date of the DATA in it into month and day, made it possible to explore more relationships. Because the current simple exploration of the relationships presented is not promising.



Split in python and form new dataset and new source “new_coupon” in SAS.



As you can see my conjecture is valid and a new significance variable appears which is the trading day, but the model construction is complex so I will look at the results of the two performed decision trees.



5.Running the first DECISION TREE reveals that 1 is not OUTCOME（Explore solutions）

```
 94  Classification Table
 95
 96  Data Role=TRAIN Target Variable=Coupon_Status Target Label=' '
 97
 98                          Target        Outcome     Frequency       Total
 99  Target    Outcome     Percentage    Percentage      Count      Percentage
100
101    0          0         66.1722         100         14008        66.1722
102    1          0         33.8278         100          7161        33.8278
103
104
105  Data Role=VALIDATE Target Variable=Coupon_Status Target Label=' '
106
107                         Target        Outcome     Frequency       Total
108  Target    Outcome     Percentage    Percentage      Count      Percentage
109
110    0          0         66.1691         100         10505        66.1691
111    1          0         33.8309         100          5371        33.8309
112
113
114
```

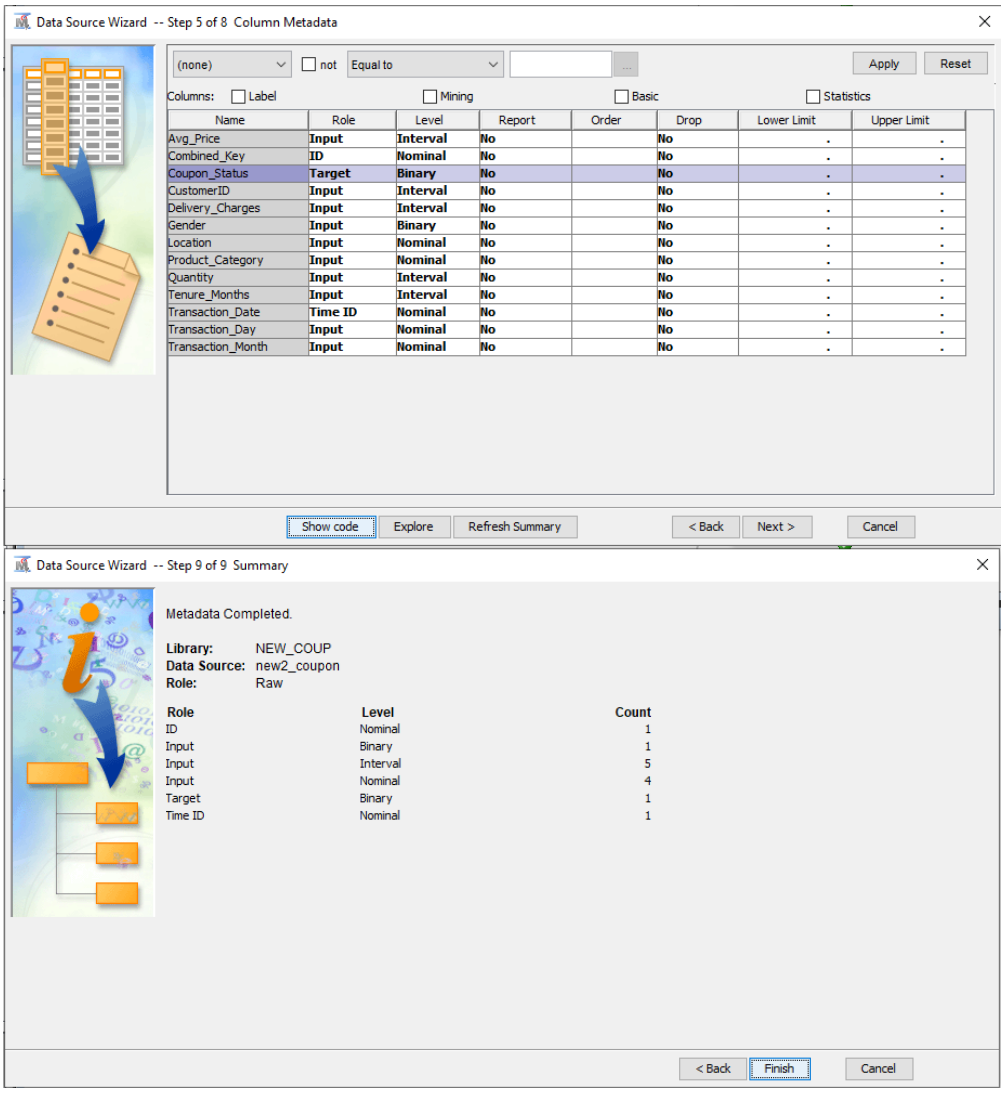
Problem1-solution based on dataset: Adjusting the data structure to continue the exploration, I found a complication in my dataset is that “CustomerID” and “TransactionID” are duplicates, so I need to create a key combination TransactionDd+Produc_SKU to uniquely identify each of the Combined_IDs. for each piece of data, which can then be used for better modeling. Then delete transactionid+Produc_SKU. Done in python.

```
data['Combined_Key'] = data['Transaction_ID'].astype(str) + "-" + data['Product_SKU']
```

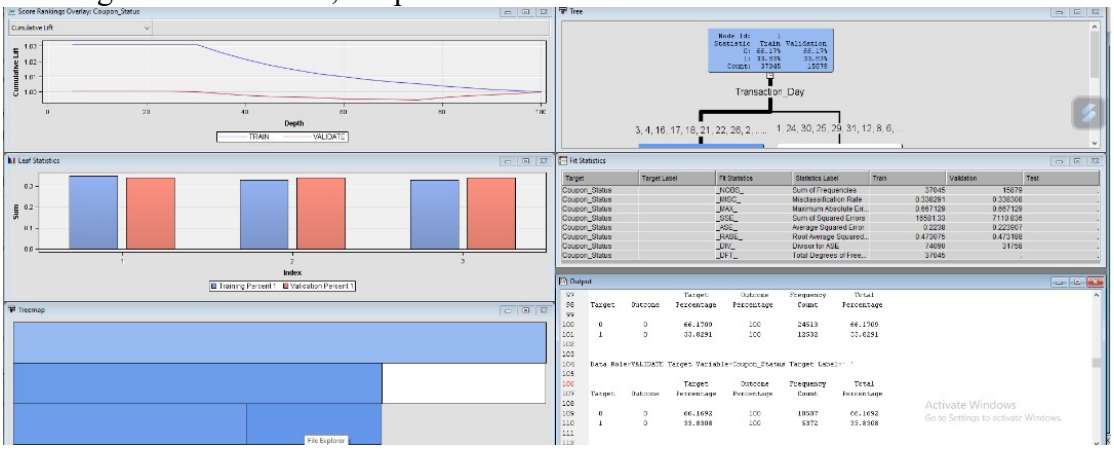
```
data.to_csv('datasetfinal_new2.csv', index=False)
```

```
data = data.drop(['Transaction_ID', 'Product_SKU'], axis=1)
```

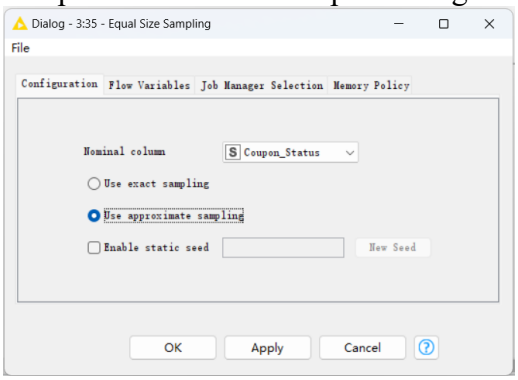
The new data variables are as follows：

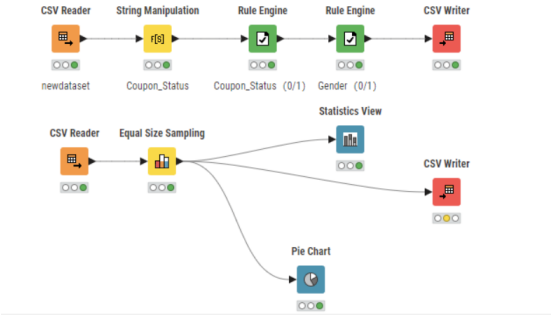


Running the decision tree, the problem is still not solved.

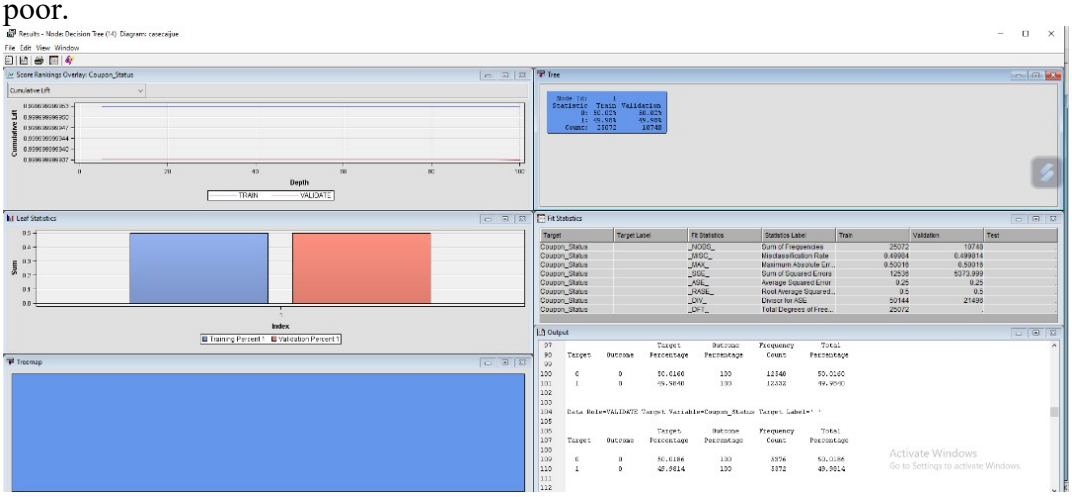


Problem2-solution based on dataset: Checked the 0 and 1 of the coupon status and found that as a TARGET it's 0 and 1 are not balanced, maybe that's why the 0 can't be read and explored, so I solved the data imbalance by exploring it. Since I am not skilled in using sas software, I completed the imbalance processing of the data in KINME.

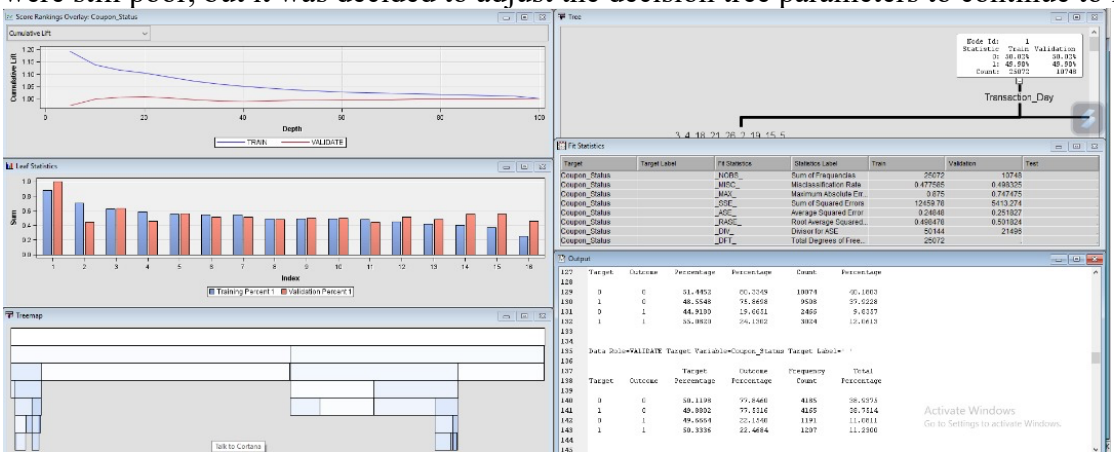




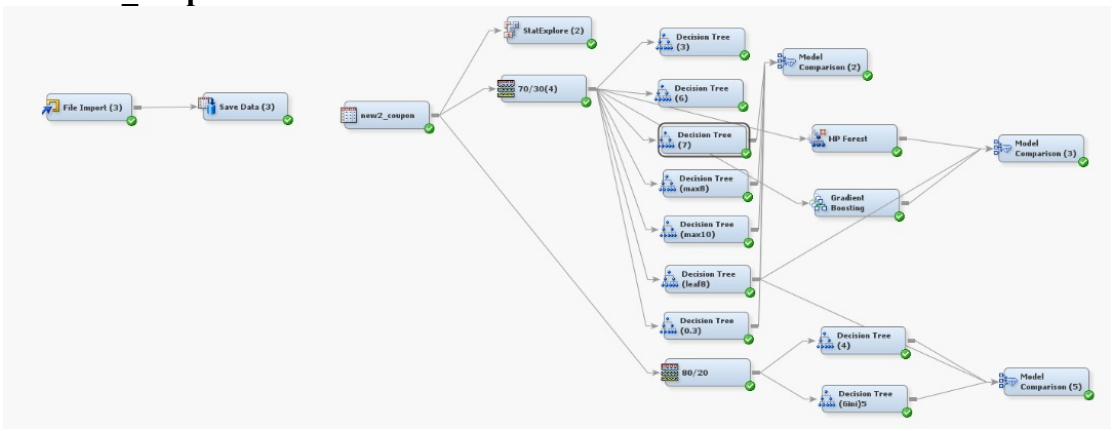
After exporting the new dataset BALANCE and repeating the above steps, the rendering is still poor.



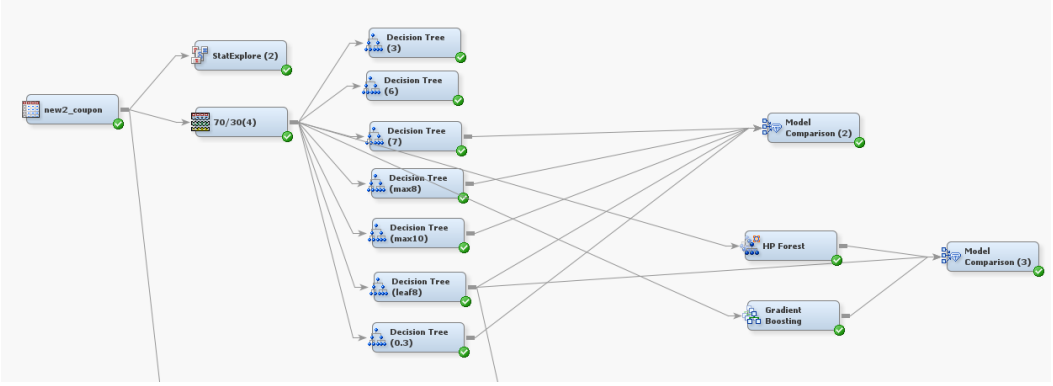
Solution3--solution based on decision tree setting. - **Resolved**
Experimenting with the third possibility,the data was too noisy for another segmentation method, using gini, it was found that a certain amount of decision making occurred although the values were still poor, but it was decided to adjust the decision tree parameters to continue to improve.



6. Explore decision tree results on both datasets.
6.1 new2_coupon



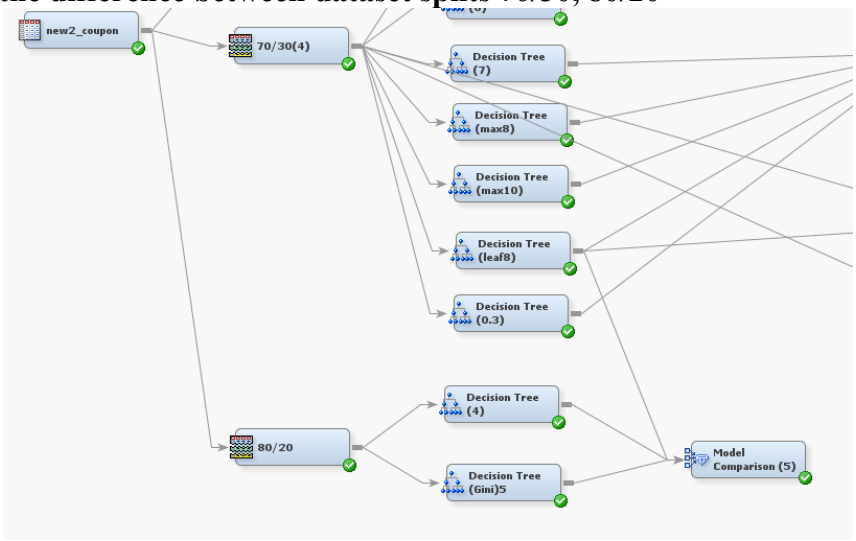
- **Data set split 70/30**
  With a 70/30 score dataset, adjusted for multiple branchleaf values and dength values, Gini leaf8 dength10 performed the best.



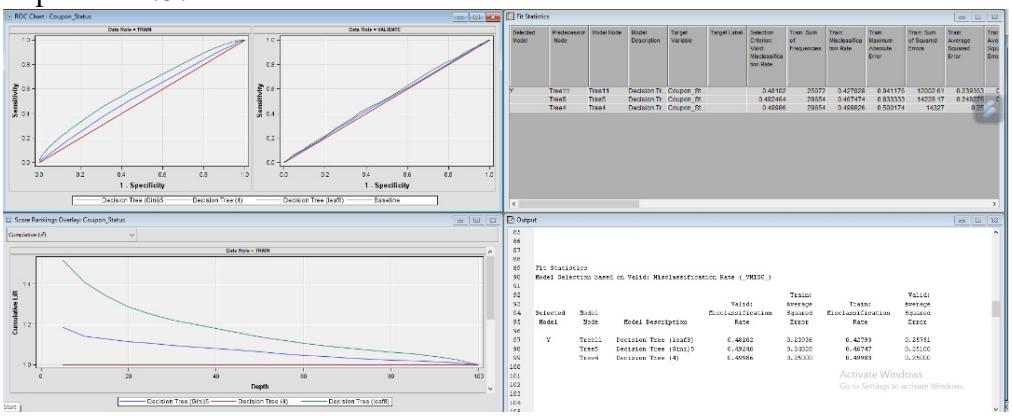
Model Comparison（2）Outcome.

Selected Model	Model Node	Model Description	Valid: Misclassification Rate	Train: Average Squared Error	Train: Misclassification Rate	Valid: Average Squared Error
Y	Tree11	Decision Tree (max10)	0.48102	0.23936	0.42793	0.25751
	Tree9	Decision Tree (max10)	0.48214	0.23923	0.43327	0.25687
	Tree10	Decision Tree (max8)	0.49088	0.24463	0.45333	0.25386
	Tree7	Decision Tree (7)	0.49833	0.24848	0.47758	0.25183

- **Compare the difference between dataset splits 70/30, 80/20**

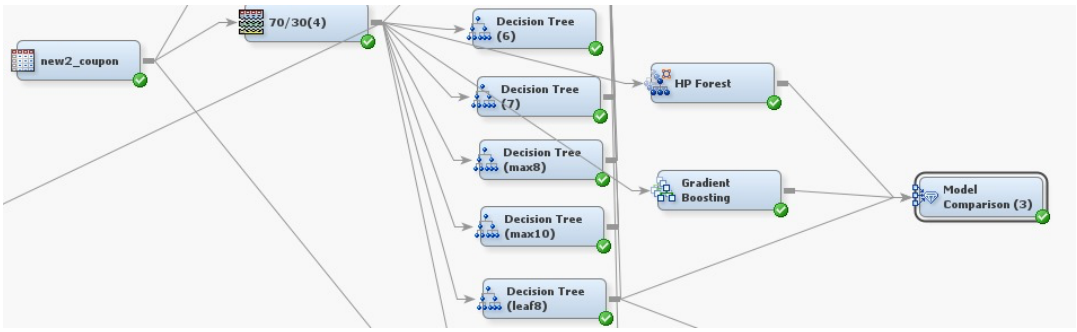


Model Comparison（5）Outcome.



It was found that splitting the size of the other dataset does not drastically affect the accuracy of the model, so it is possible to use 70/30 to continue exploring, since splitting does not make sense.

- **Apply Bagging and Boosting, using the Random Forest algorithm as a Bagging example.**



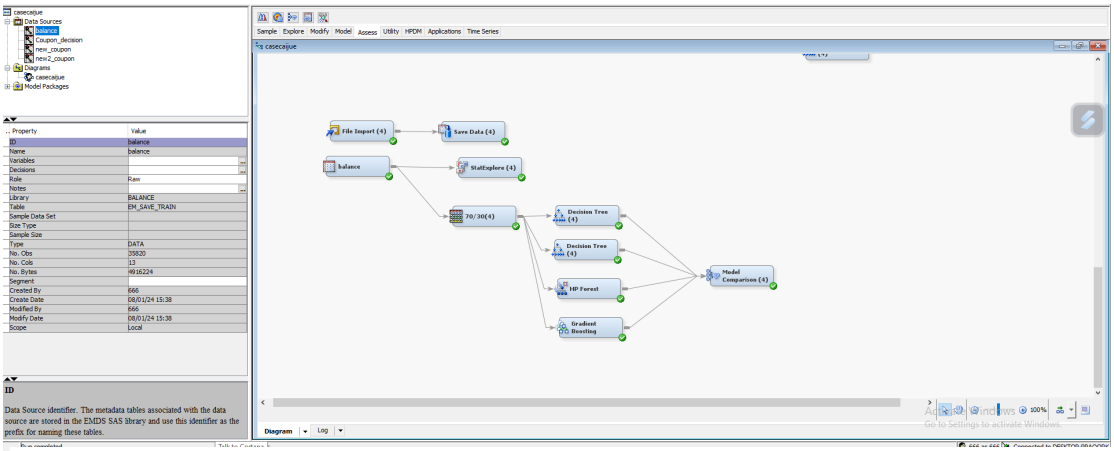
Model Comparison（3）Outcome.

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

Selected Model	Model Node	Model Description	Valid: Misclassification Rate	Train: Average Squared Error	Train: Misclassification Rate	Valid: Average Squared Error
Y	Treell	Decision Tree (leaf8)	0.48102	0.23936	0.42793	0.25751
	Boost	Gradient Boosting	0.50502	0.24981	0.48413	0.25012
	HPDMForest	HP Forest	0.50735	0.24970	0.48062	0.25025

Adding bagging and boost tends to make, accuracy improve, but sadly it didn't in my data project. Suggesting that I need to start this whole project with a review of the meaning of the dataset I'm exploring and whether the categorization really makes sense.

6.2 balance



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

Selected Model	Model Node	Model Description	Valid: Misclassification Rate	Train: Average Squared Error	Train: Misclassification Rate	Valid: Average Squared Error
Y	Tree13	Decision Tree (4)	0.48809	0.23641	0.41644	0.26199
	Boost2	Gradient Boosting	0.49070	0.24759	0.44241	0.25009
	Tree12	Decision Tree (4)	0.49116	0.23888	0.42266	0.25973
	HPDMForest2	HP Forest	0.51107	0.24967	0.47818	0.25025

The data after balancing with KNIME is also still not good, there are many reasons for this, it could be that the specific technique used for balancing doesn't work and exploring this I think I need to go back to the beginning and reexamine all my work.

General overview of the process: