Babu Banarasi Das University

Case Study on

Predictive Analysis of Car Price Segmentation Using SPSS

(BCADSN15301)

Project Overview

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Project Definition and Goals

Definition: This is a Classification Modeling project using the CHAID Decision Tree algorithm to predict a car's price category (High vs. Standard) based on its features.

Purpose: To identify which car attributes (like Mileage, Engine Size, and Year) are the most significant drivers of high market value, achieving a reliable price prediction model.

Outcomes/Learning:

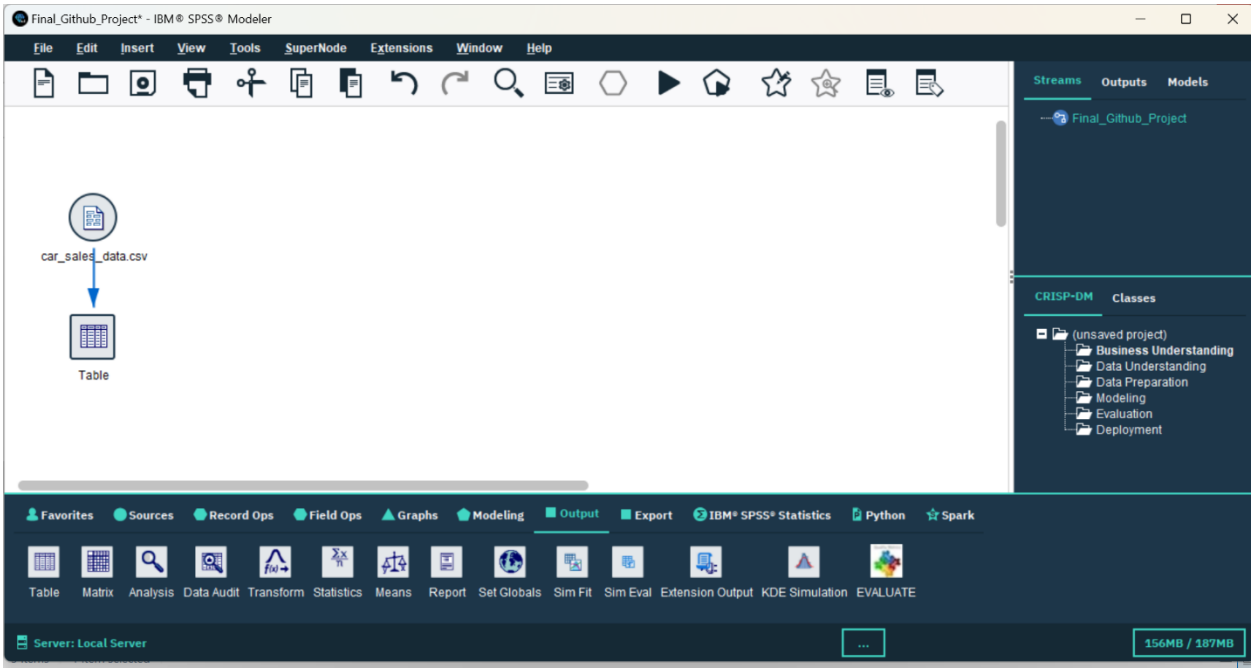
Data Transformation: Learned to use the Derive node to convert a continuous variable (Price) into a categorical Flag (Price_Category) suitable for classification models.

Model Building: Applied the CHAID node to automatically identify and build decision rules based on the strongest predictor variables in the dataset.

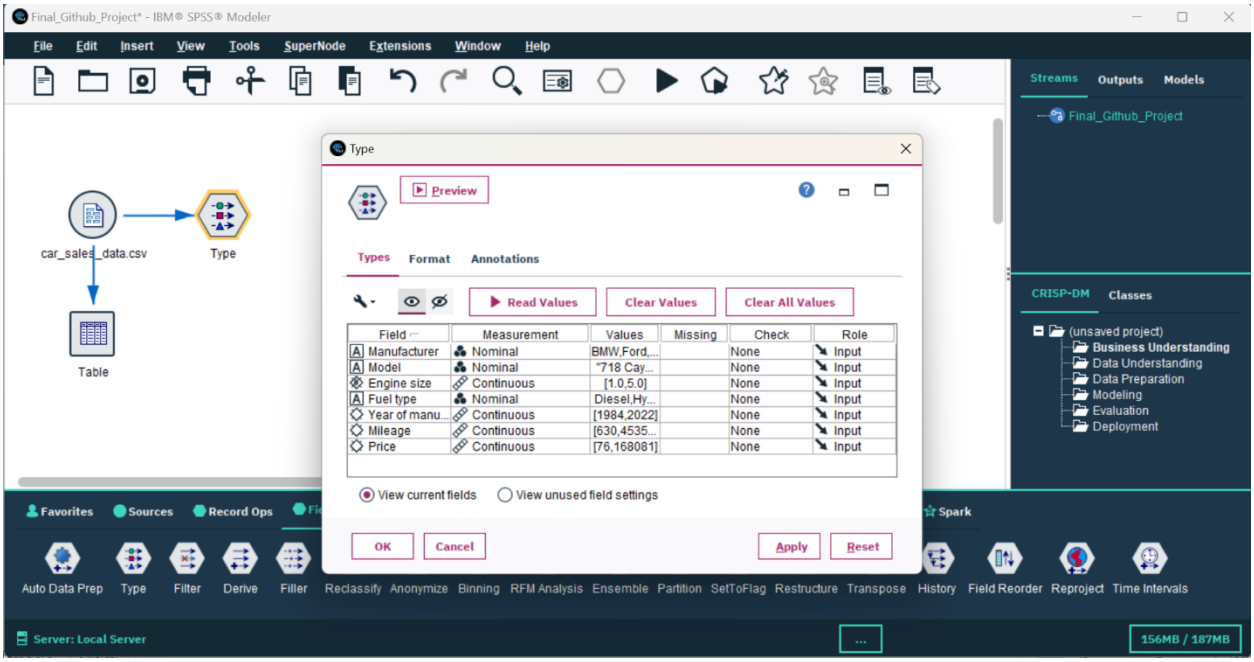
Required Tool: IBM SPSS MODELER TOOL

Working: - In this Project we will use 'car_sales_data.csv' dataset and perfom Car Price Classification and Segmentation Analysis. The following steps are going to be executed in IBM SPSS MODELER:

Step 1: From Sources we will select Var. File node and import our dataset (car_sales_data.csv). After that select Table node from output and then connect the dataset with the table to preview the output.



Step 2: Now we will use Type Node from Field Ops and connect it to car_sales_data.csv node to Read Values meaning it reads the data and automatically determines the measurement level and values for each field.

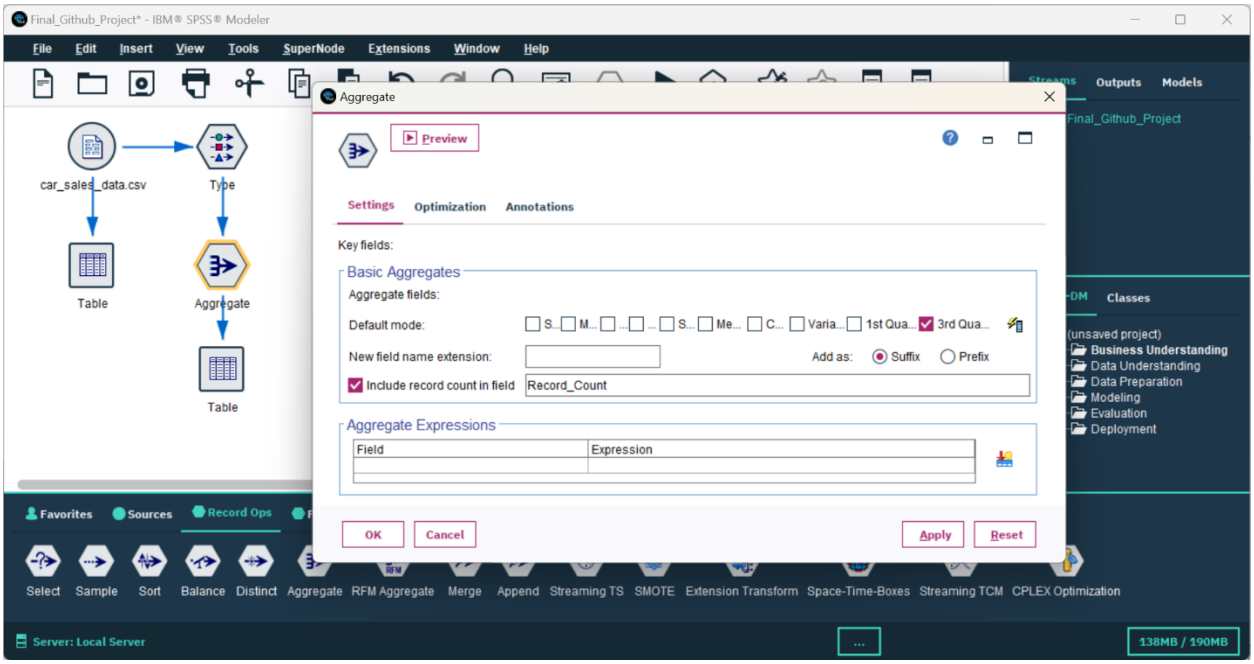


Step 3: We will Add the Aggregate Node (from Record Ops) and calculate the 3rd Quartile (75th Percentile) of the car price.

• The output shows a 3rd Quartile value of $19,027.

• This means 75% of all cars in the dataset sold for this price or less.

• We use this value to set the cutoff, defining the ‘High Price’ category as the top 25% of the market value.


Final_Github_Project* - IBM® SPSS® Modeler
File Edit Insert View Tools SuperNode Extensions Window Help
car_sales_data.csv
Type
Table
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Settings Optimization Annotations
Key fields:
Basic Aggregates
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Default mode:
New field name extension:
Add as: Suffix Prefix
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Classes
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Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Favorites Sources Record Ops
Select Sample Sort Balance Distinct Aggregate RFM Aggregate Merge Append Streaming TS SMOTE Extension Transform Space-Time-Boxes Streaming TCM CPLEX Optimization
Server: Local Server
138MB / 190MB

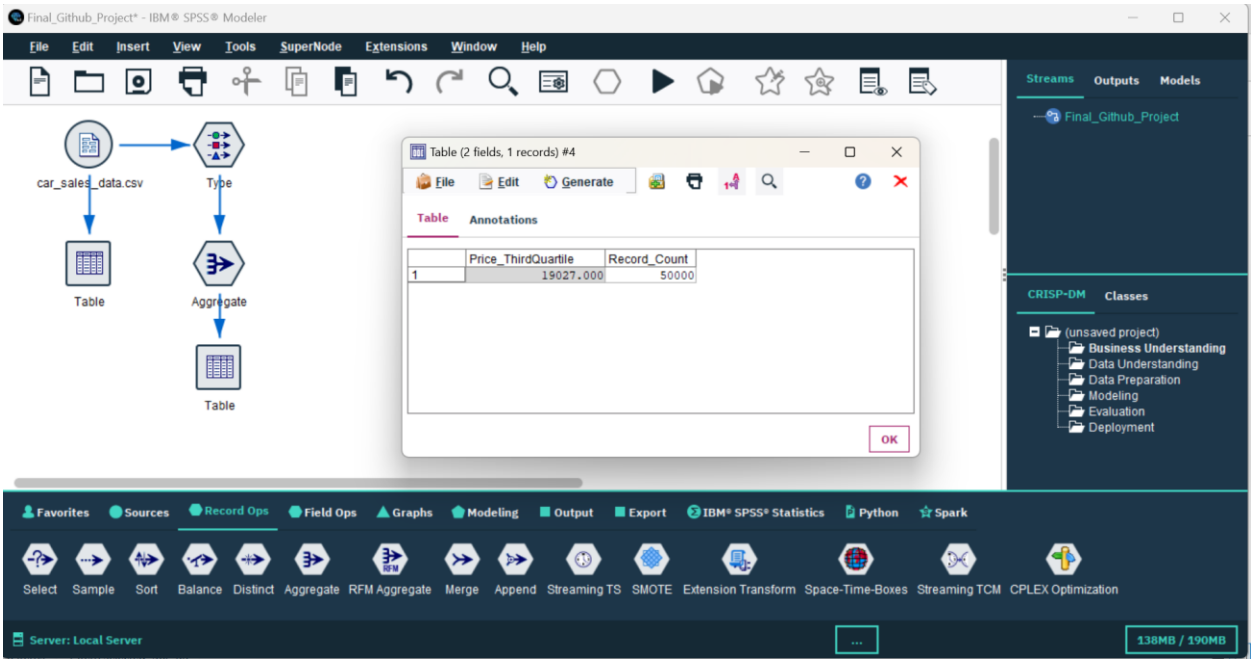
Final_Github_Project* - IBM® SPSS® Modeler
File Edit Insert View Tools SuperNode Extensions Window Help
car_sales_data.csv
Type
Table
Aggregate
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Table (2 fields, 1 records) #4
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Table Annotations
Price_ThirdQuartile
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Business Understanding
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Data Preparation
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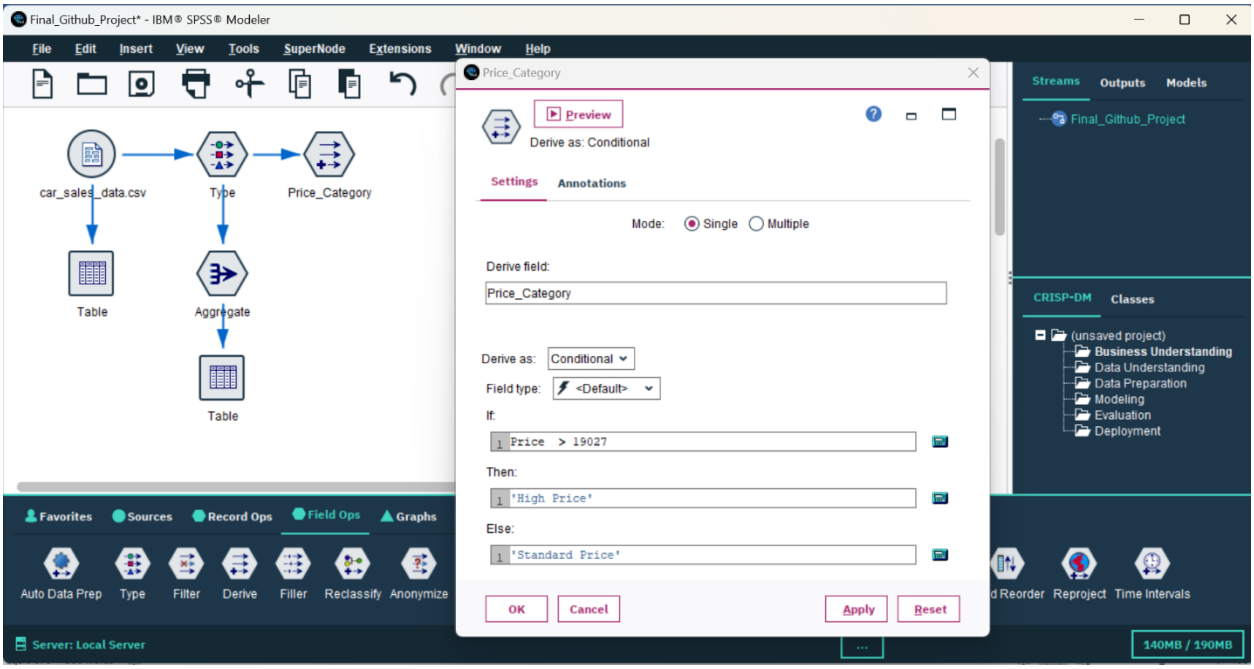
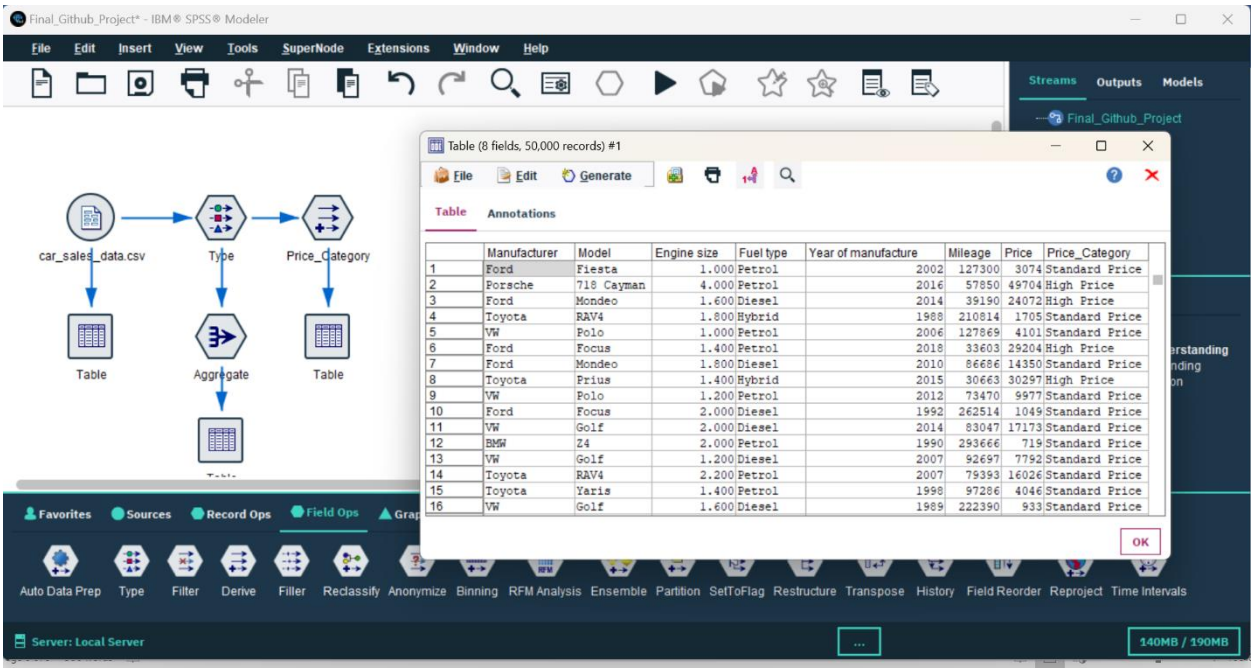
Favorites Sources Record Ops Field Ops Graphs Modeling Output Export IBM® SPSS® Statistics Python Spark
Select Sample Sort Balance Distinct Aggregate RFM Aggregate Merge Append Streaming TS SMOTE Extension Transform Space-Time-Boxes Streaming TCM CPLEX Optimization
Server: Local Server
138MB / 190MB

Step 4: Now we will take the Derive Node from Field Ops and connect it to type node and in the Derive Node we will do “Derive as: Conditional and Field Type: Default” ***.If*** Price > 19027 ***Then*** 'High Price' ***Else*** 'Standard Price'

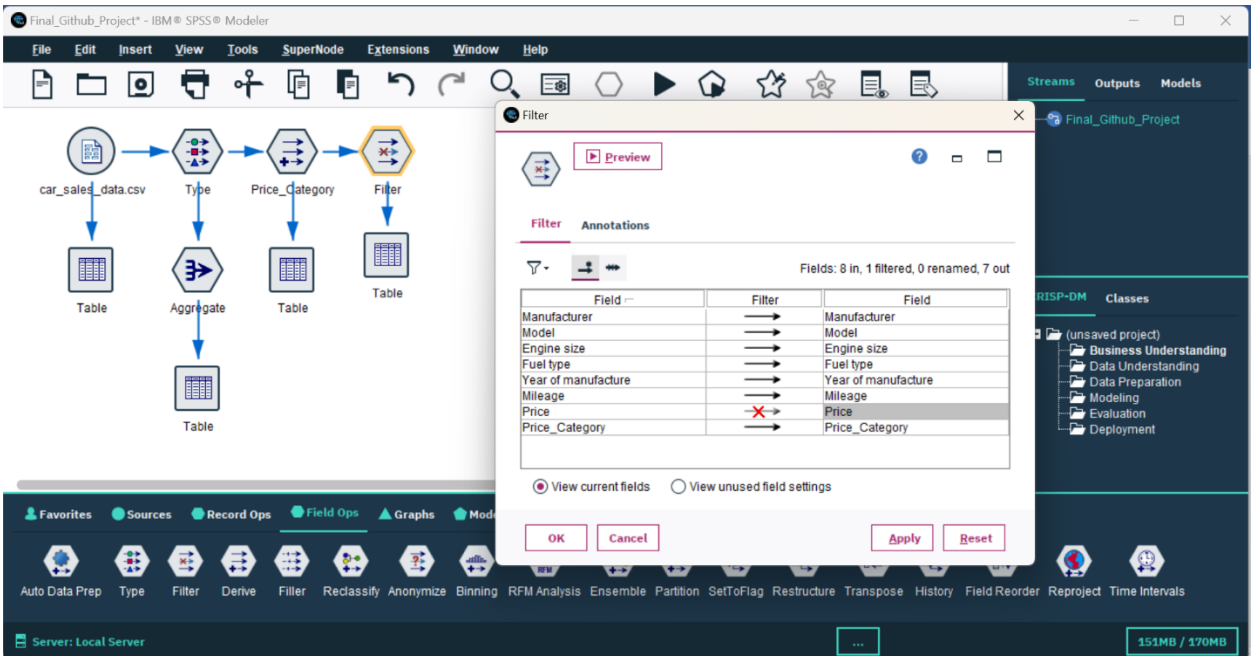
Apply and then connect a table and run it to see the output

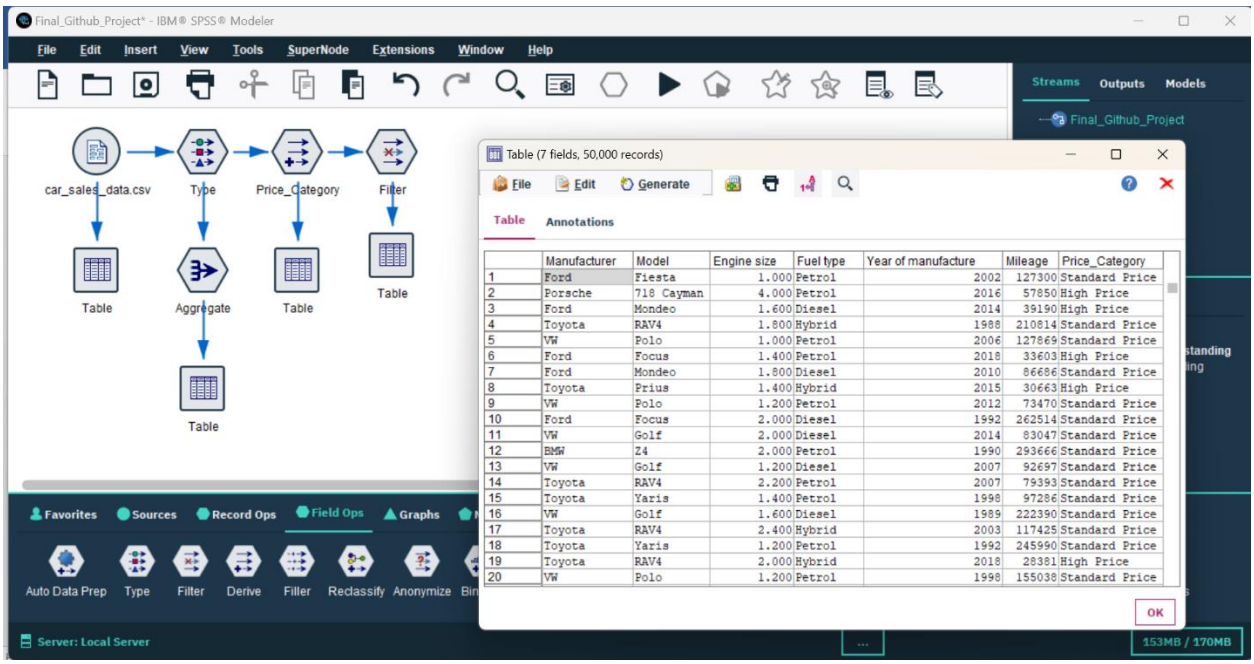




Step 5: Now we will use Filter Node from Field Ops and connect it to the Derive Node (Price_Category). In the Filter Node we will Cross (or deselect) the Price field.

And then connect a table and run.



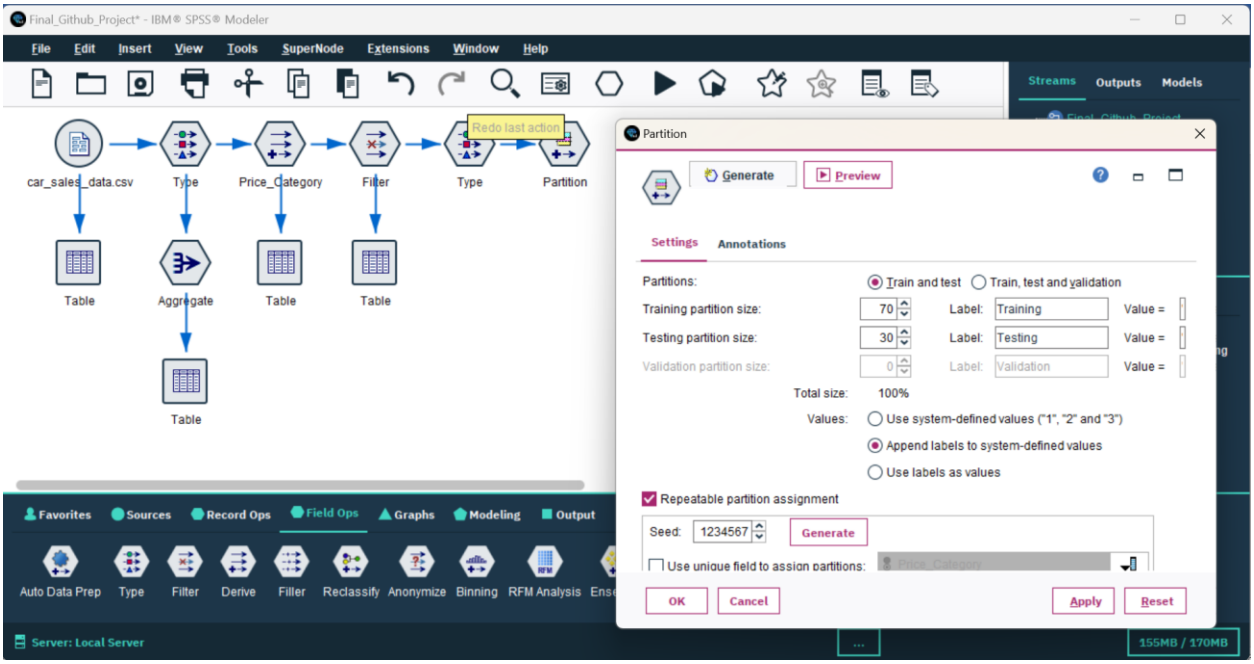


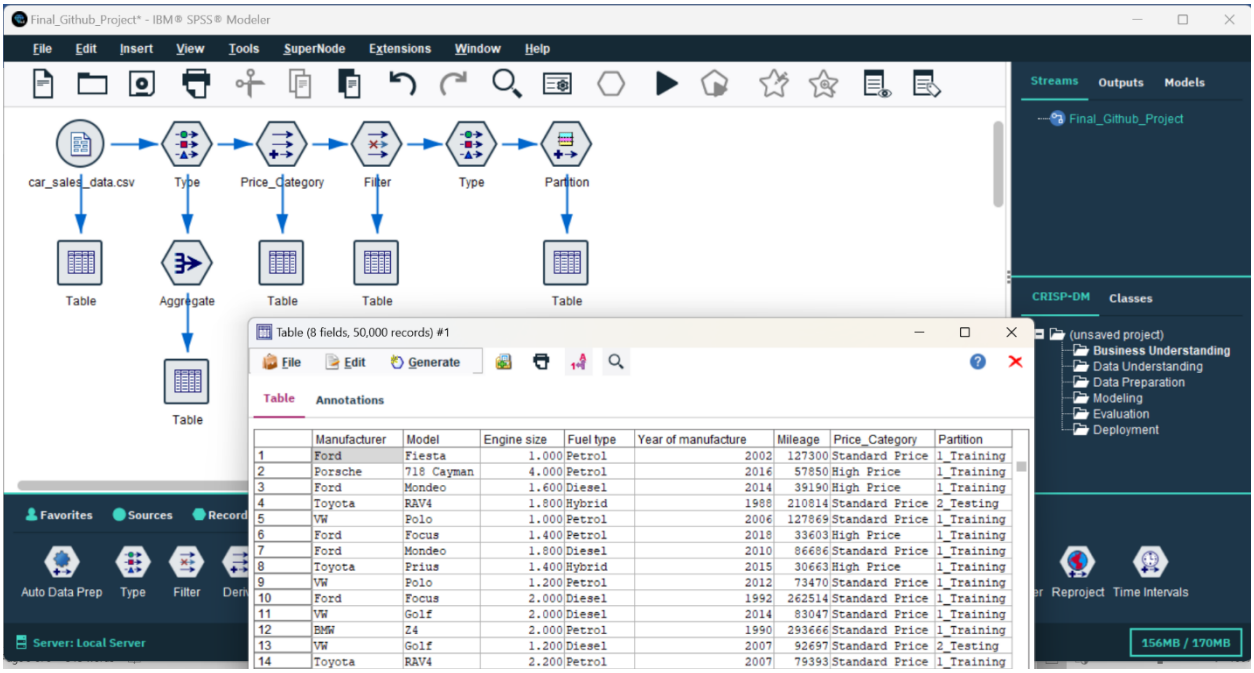
Step 6: We will now add 2nd Type Node from Field Ops and connect it to our previous filter node .Now in the Type Node we will change the role of 'Price_Category' as Target and every other as Input.

Step 7: Now we will add Partition node from Field Ops and connect it to the previous or 2nd Type Node. In the Partition Node we will split the data into a 70% Training Set and a 30% Testing Set.

(This Division is basic for correctly validating the model's accuracy on data it has not processed yet.)

And then Connect a Table to see the output.



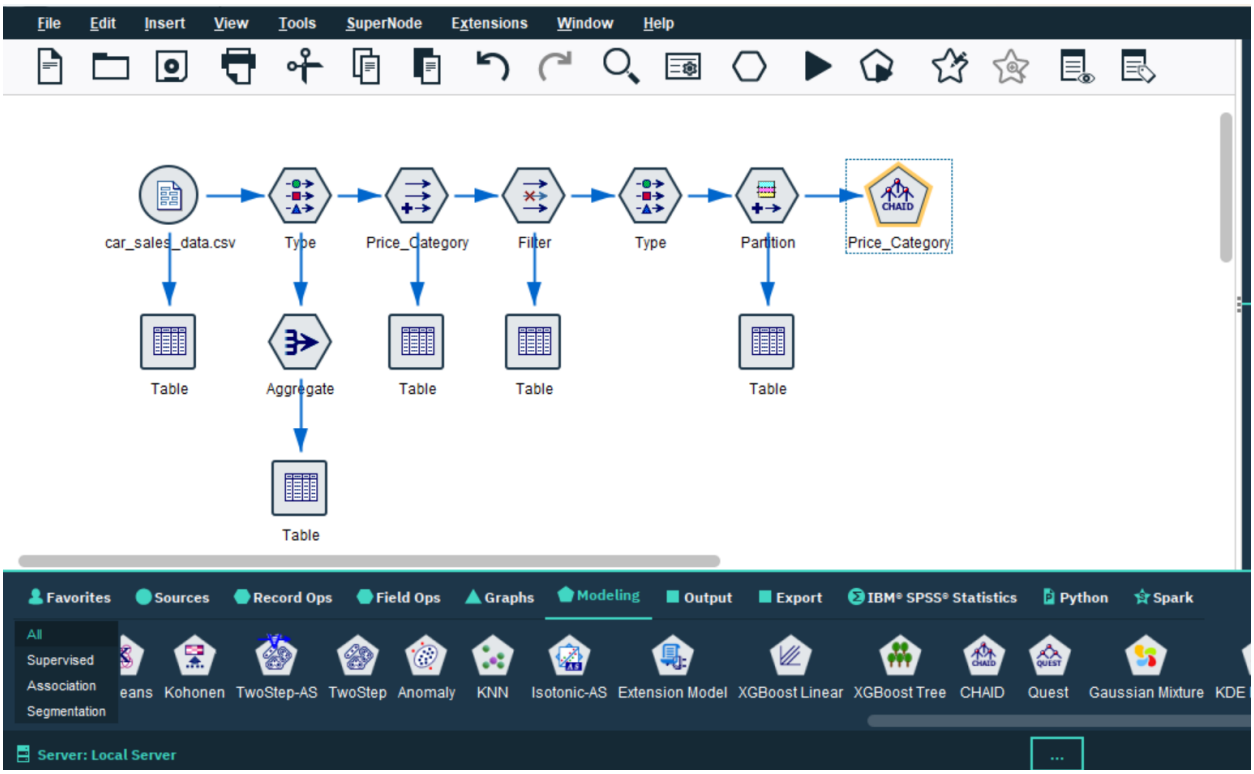


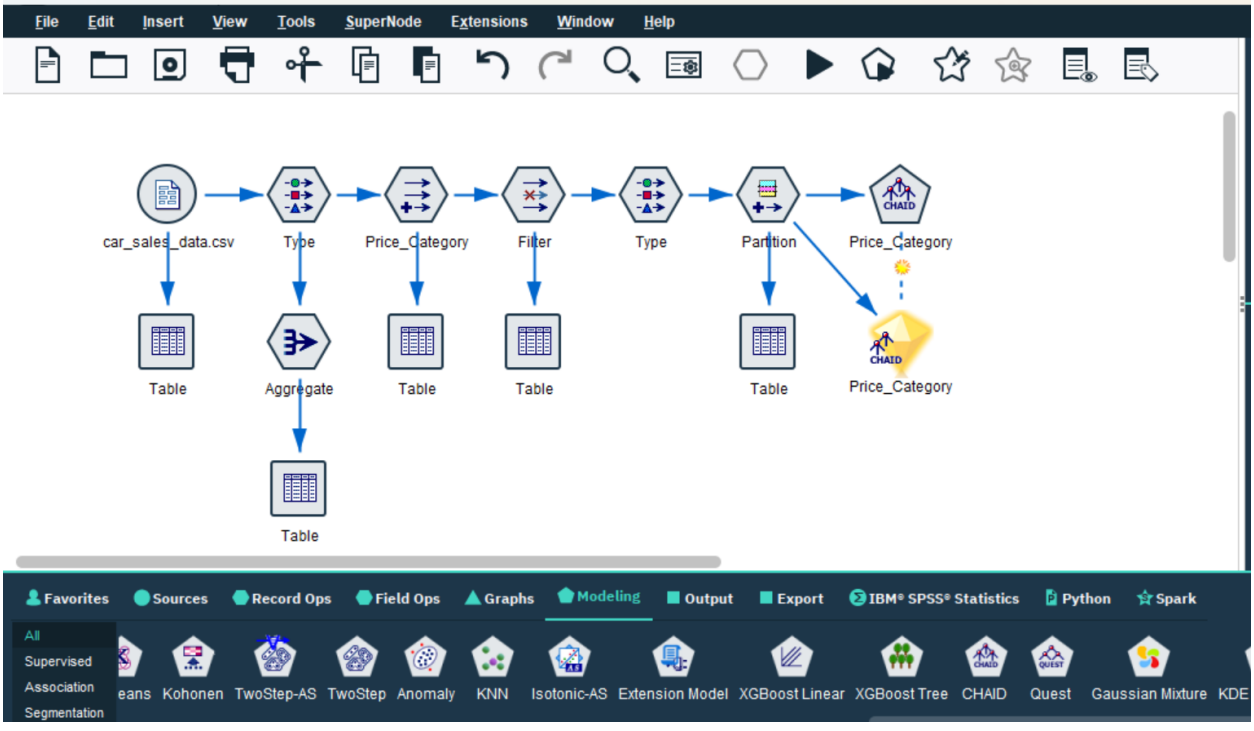
	Manufacturer	Model	Engine size	Fuel type	Year of manufacture	Mileage	Price_Category	Partition
1	Ford	Fiesta	1.000	Petrol	2002	127300	Standard Price	1_Training
2	Porsche	718 Cayman	4.000	Petrol	2016	57850	High Price	1_Training
3	Ford	Mondeo	1.600	Diesel	2014	39190	High Price	1_Training
4	Toyota	RAV4	1.800	Hybrid	1988	210814	Standard Price	2_Testing
5	VW	Polo	1.000	Petrol	2006	127869	Standard Price	1_Training
6	Ford	Focus	1.400	Petrol	2018	33603	High Price	1_Training
7	Ford	Mondeo	1.800	Diesel	2010	86686	Standard Price	1_Training
8	Toyota	Prius	1.400	Hybrid	2015	30663	High Price	1_Training
9	VW	Polo	1.200	Petrol	2012	73470	Standard Price	1_Training
10	Ford	Focus	2.000	Diesel	1992	262514	Standard Price	1_Training
11	VW	Golf	2.000	Diesel	2014	83047	Standard Price	1_Training
12	BMW	Z4	2.000	Petrol	1990	293666	Standard Price	1_Training
13	VW	Golf	1.200	Diesel	2007	92697	Standard Price	2_Testing
14	Toyota	RAV4	2.200	Petrol	2007	79393	Standard Price	1_Training

Step 8: Now from Modelling , we will add a CHAID Node and connect it to the Partion Node. In the CHAID Node we will make Price_Category as Target and else as Inputs.

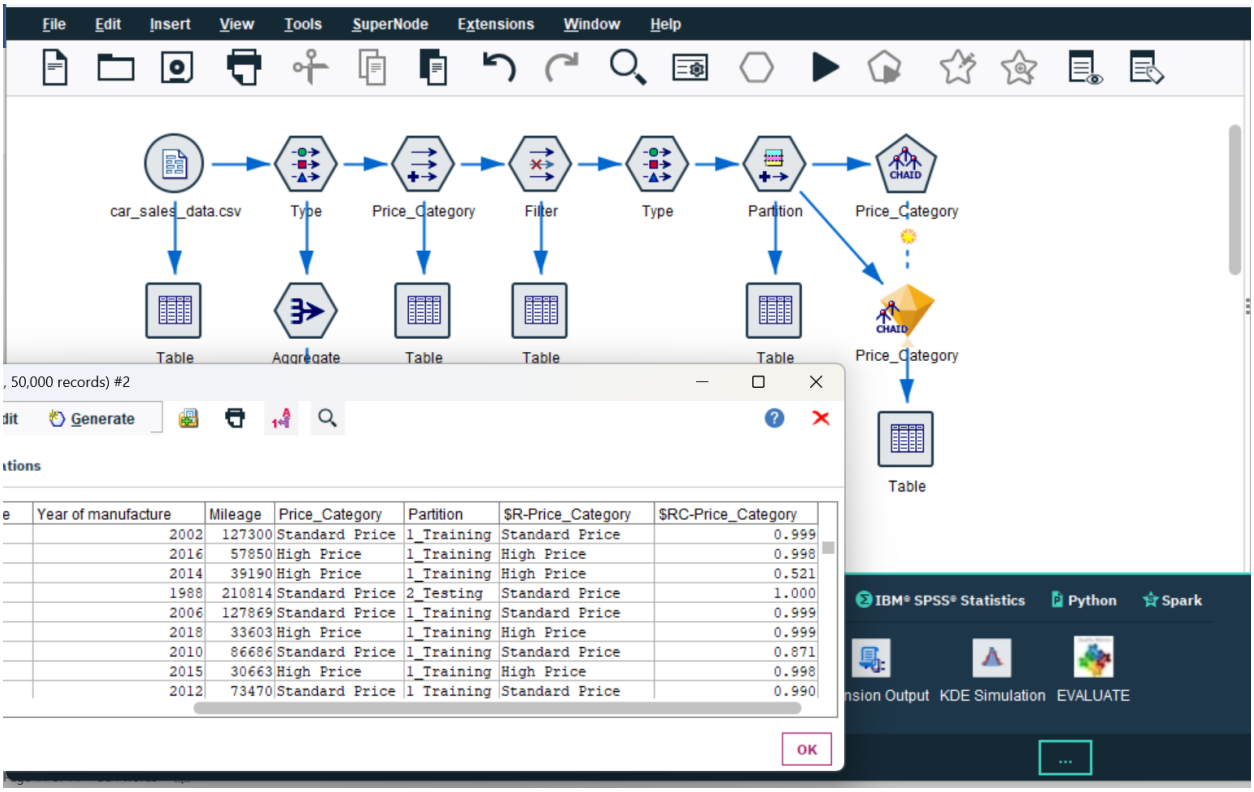
After Running it .It will automatically generate a CHAID NUGGET

(The Resulting Decision Tree Identified Mileage as the single most important factor for Predicting the price Category)



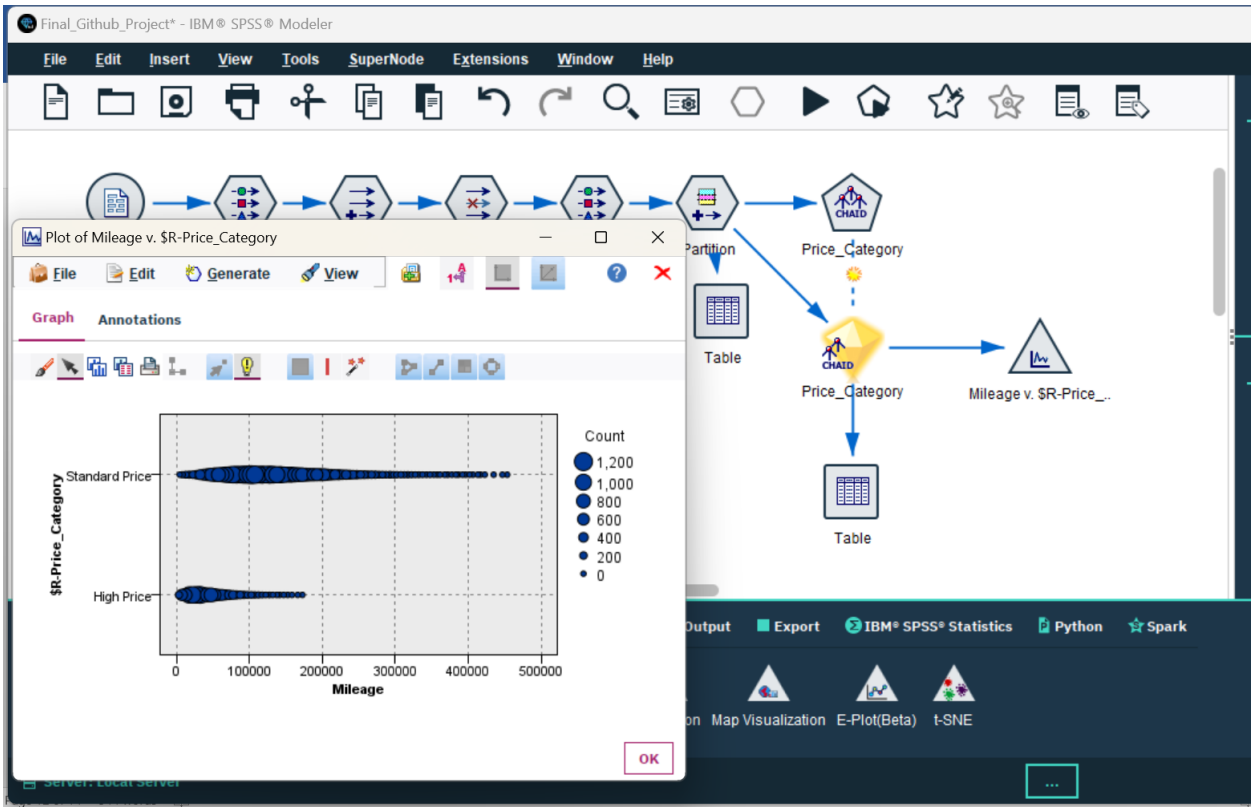


After connecting a Table to Output Node, We can see two new columns $R-Price_Category(Prediction) and $RC-Price_Category(Confidence)



STEP 9: We will connect a Plot Node from Graphs to the CHAID Nugget and in the plot node we will put Mileage in the X-Field and $R-Price_Category in Y-Field to visualize Predicted Category vs. Mileage.

The graph clearly showed that High Price predictions are concentrated in the low mileage range, validating the model's internal logic.



STEP 10: And at Last, We will add Analysis Node from Output and connect it to the CHAID Nugget and run it.

[Analysis Node (Confusion matrix) is to see the Classification Accuracy (the percentage of records the model correctly predicted in your testing partition)].

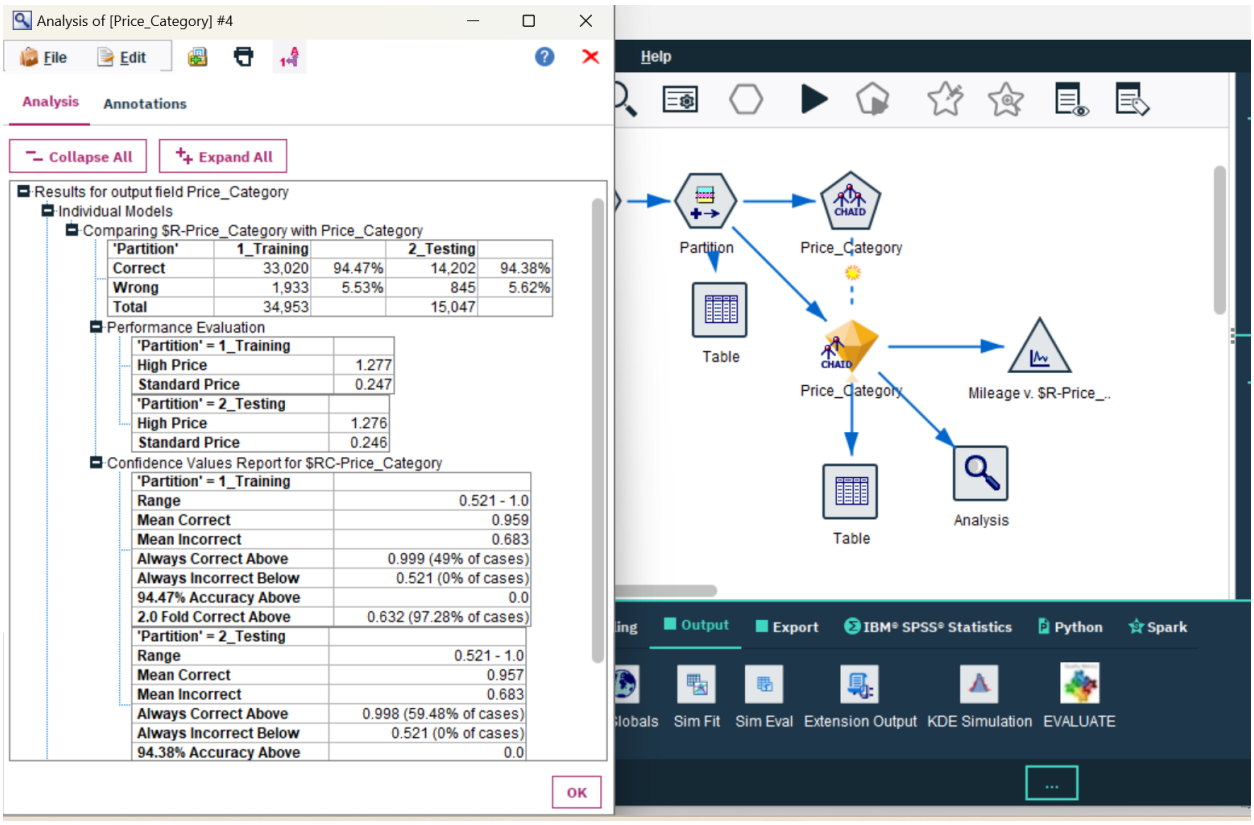
After running the Analysis Node we can see the result.

Overall Accuracy – 94.27% **-**The model correctly classified the Price_Category for over 94% of all test records, indicating excellent predictive performance.

High Price Accuracy – 86.30% - The model correctly identified 86.30% of the actual 'High Price' cars. (This is the Recall for the 'High Price' class).

Standard Price Accuracy – 96.80% - The model correctly identified 96.80% of the actual 'Standard Price' cars.

Total Errors – 877 records - Out of 15,300 test records, the model made 877 errors (506 False Negatives + 371 False Positives).



Conclusion

The CHAID model achieved high overall accuracy (94.27%). While it is slightly better at identifying 'Standard Price' cars (96.80\%), it still has a very strong 86.30% success rate in correctly identifying the target 'High Price' segment. This demonstrates that the features selected by the model are highly effective at differentiating high-value vehicles.