Data Preparation with Claim Fraud Dataset/ SAS Enterprise Miner

Didem B. Aykurt

Colorado State University Global

MIS530; Predictive Analytics

Dr.Jennifer Catalano

January 29, 2023

Data Preparation Using the SAS Enterprise Miner

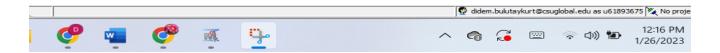
When I start to use a new programming language or software, I am always searching for why I need it or the pros and cons of this program. The first time I faced it, it was not fast and easy to use. They should update the program. Also, most learning tools were updated a few years ago; video or other devices do not support the new version. It is so complicated. The program has limited learning sources online, which tells me a lower percentage of people use this software program.

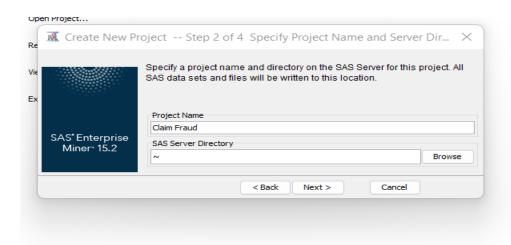
Searching for the SAS Enterprise Miner is a solution to creating accurate predictive and descriptive models on large volumes of data across different sources in the organization. (Pat Research, 2021) Some business applications are for detecting fraud, minimizing risk and resource demands, reducing asset downtime and campaigns, and reducing customer attrition—the most popular category used for predictive analytics. Let's dive deep into SAS Enterprise Miner data processing step by step. There are four components for the predictive creation model in SAS Enterprise Miner:

Creating the Project File

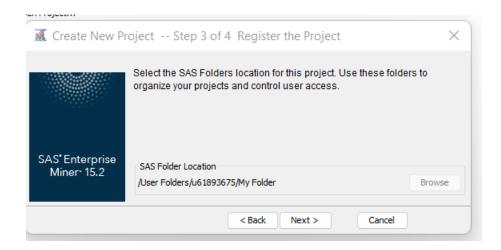
First launched, the Welcome screen appears. Create a new project, select New Project, and open new windows. I entered the project name "Claim Fraud," and the SAS Server Directory showed where the file was saved. I left the automatic field location and finished.





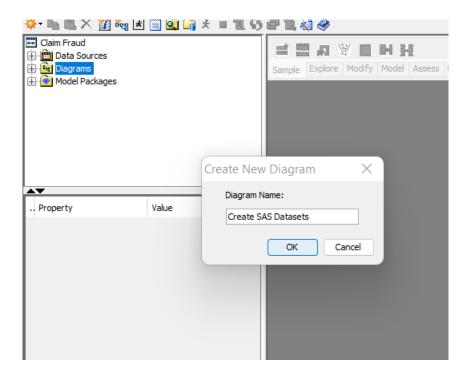


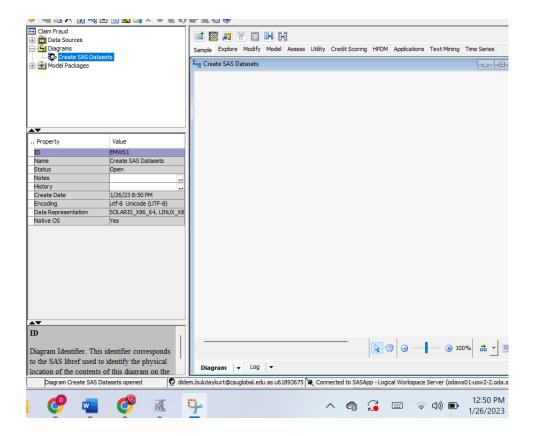




Create the Diagram

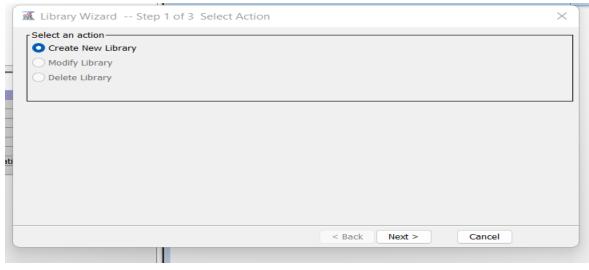
When the project window opens, the left side has a project panel list; right-click Diagrams and select Create Diagram, then pop up the new window named the diagram "Create SAS Datasets."

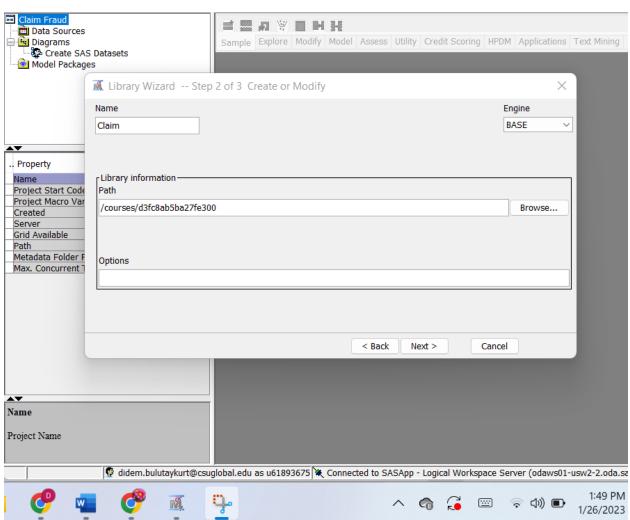




Create the Library

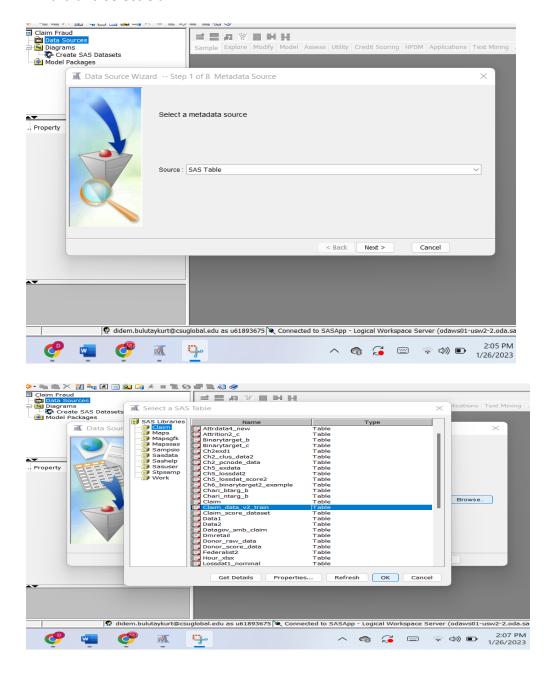
The SAS library creates the directory location of the stored SAS data files. To build a SAS library, click on the File Menu-New-Library, then the library wizard opens, and I named "Claim" the used library path as /courses/d3fc8ab5ba27fe300 next and finished. This library path already loaded the claim dataset.

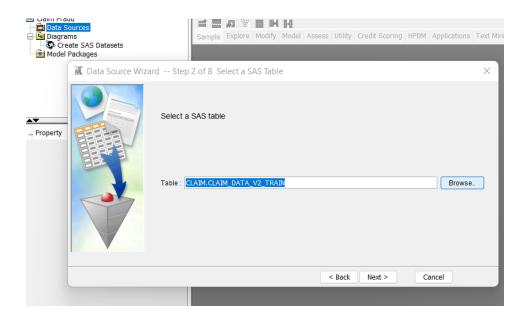


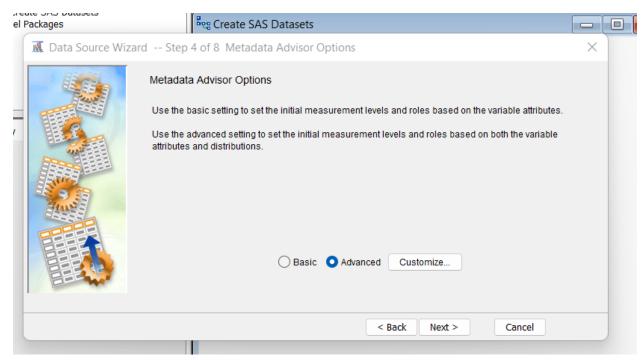


Create Data Source

Now, I have four components to start creating the data sources. I used the auto insurance claim data set that had already loaded. To make the data sources, click the File menu-New-Data Source, or the left side Project panel has Data Sources; Right click, then pop up Data Sources Wizard and select Claim.

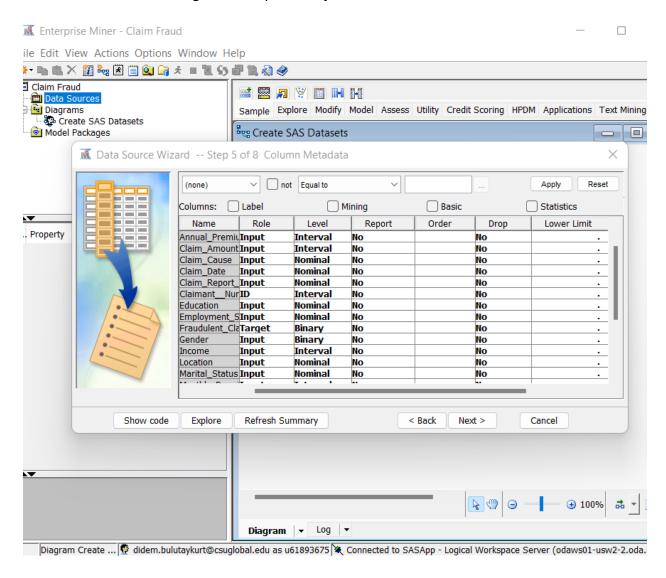


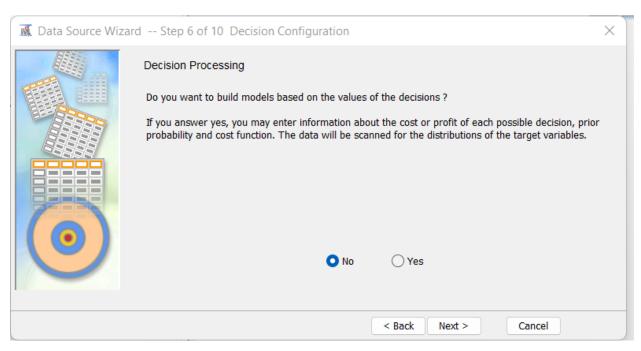


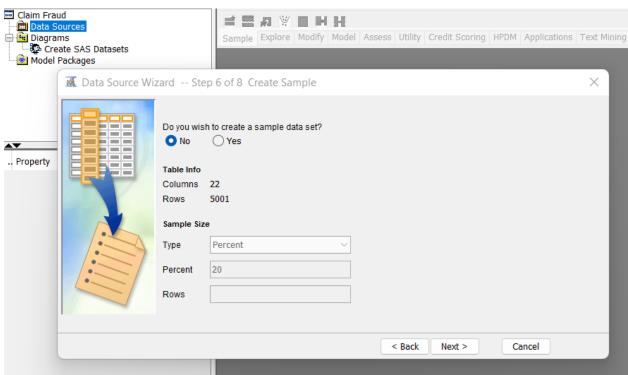


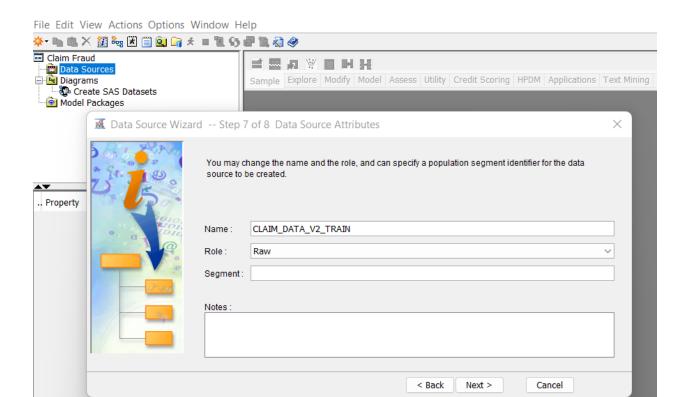
To change roles and levels, the next Metadata Advisor Option. The Fradulent_Claim variable's column Role change Input to Target as a dependent variable; it is binary (yes/no). The Claimant_Number's Role column changed Input to ID variable. The state variable will not be

used in the model as changed Role Input to Reject.

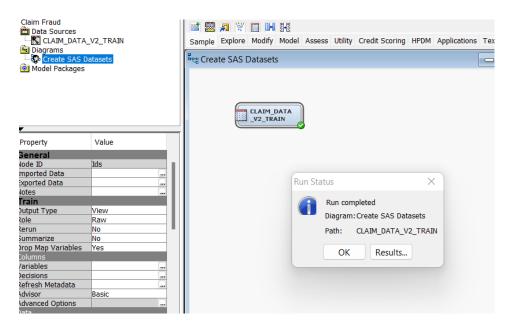


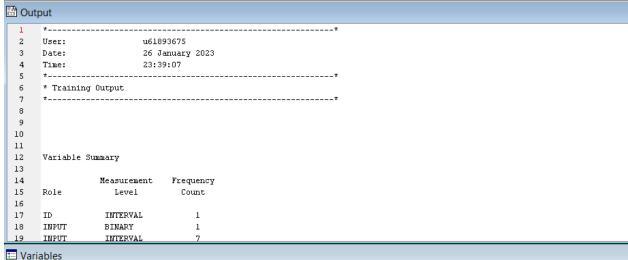






The next step is I drag the CLAIM_DATA_V2_TRAIN from the Project Panel to the Diagram
Create SAS Datasets in the workspace. Then right-click on the node and RUN. Two ways to look
at results. One is that the end of the run window has a result option or right-click on the dataset
and Result.

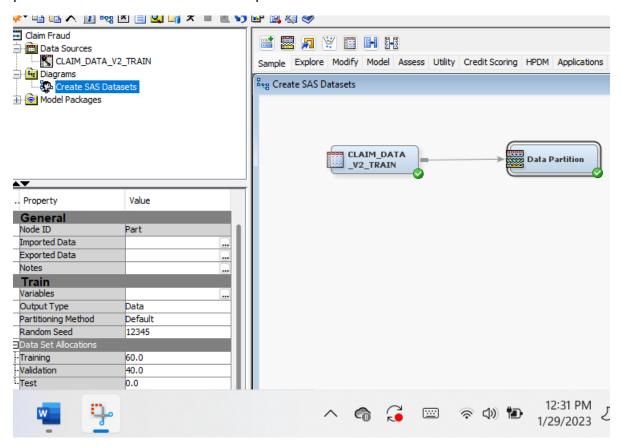




El valiables									
Role	Measurement Level	Order							
Input	Interval								
Input	Interval								
Input	Nominal								
Input	Nominal								
Input	Nominal								
ID	Interval								
Input	Nominal								
Input	Nominal								
Target	Binary								
Input	Binary								
Input	Interval								
Input	Nominal								
Input	Nominal								
Input	Interval								
Input	Interval								
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Rejected	Nominal								
	Input	Input Interval Input Interval Input Nominal Input Nominal Input Nominal Input Nominal ID Interval Input Nominal Input Binary Input Interval							

Data Partition

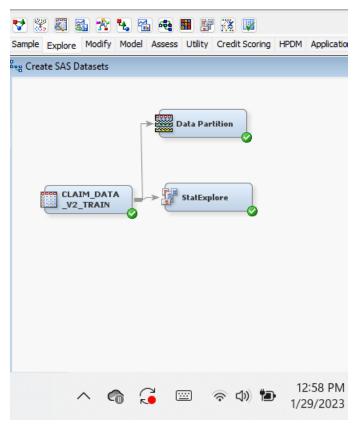
The data set divides the dataset into two or three parts: training is used to build the model, validation checks the model's accuracy, and testing partition tests the model. To create the section, click the Sample tab, then drag the Data Partition node onto the process flow. Finally, connect the Data Partition node to the CLAIM_DATA_TRAIN node. I divided the training partition into 60% and the validation partition into 40%.

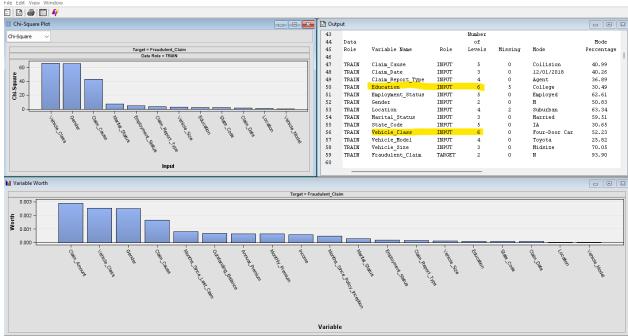


Data Exploration

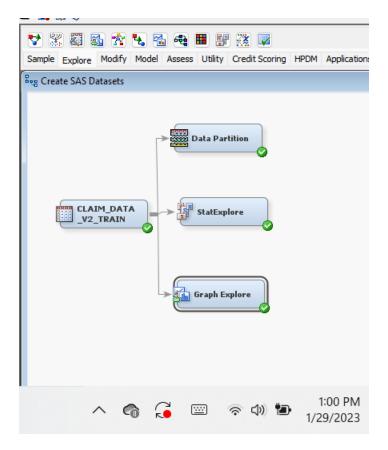
The StatExplore node shows the data summary and identifies the missing values. The Graph Explore node helps to see data point behavior by creating a histogram, stem-and-leaf plots, and box plot; both nodes are significant for descriptive statistics.

Click the Explore tab, then drag the StatExplore node onto the process flow. Finally, connect the StatExplore node to the CLAIM_DATA_TRAIN node and right-click on the node-run.



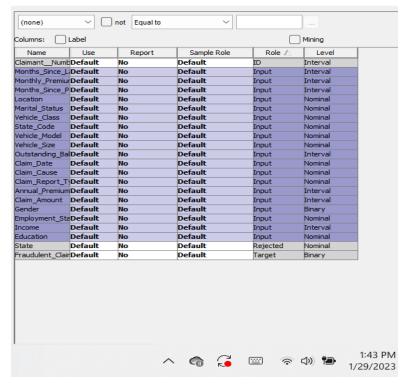


The Graph Explore node; Click the Explore tab, then drag the Graph Explore node onto the process flow. Connect the Graph Explore node to the CLAIM_DATA_TRAIN node and right-click on the node-run.

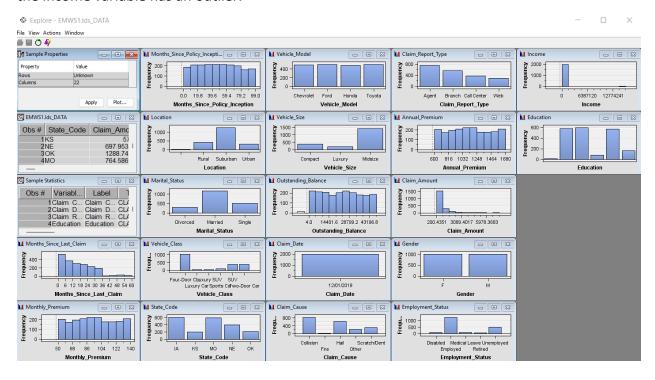


After running the Graph Explore node, right-click and select Edit Variable. For sorting by column, click on the Role column title to sort by Role. For example, to determine all the input variables you want, click the Marital_Status variable name, hold the shift down, and click on Education.



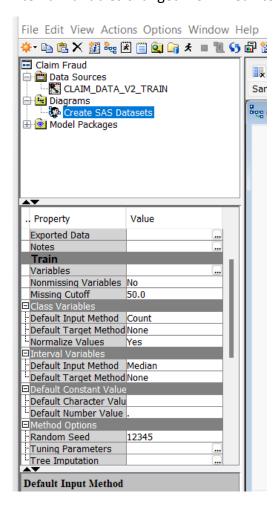


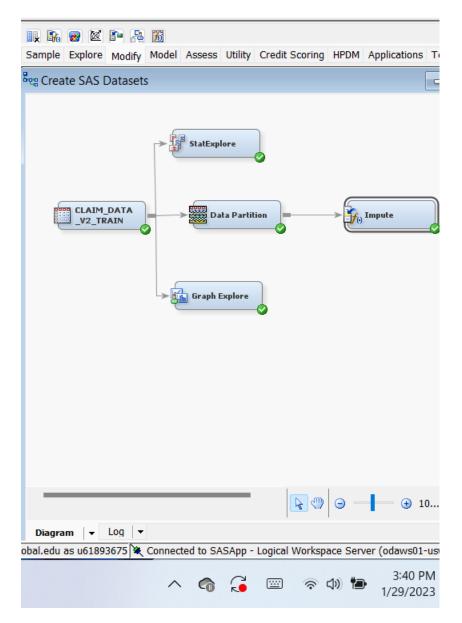
Click the Explore button, and a new window displays a histogram of all the input variables. And the Income variable has an outlier.



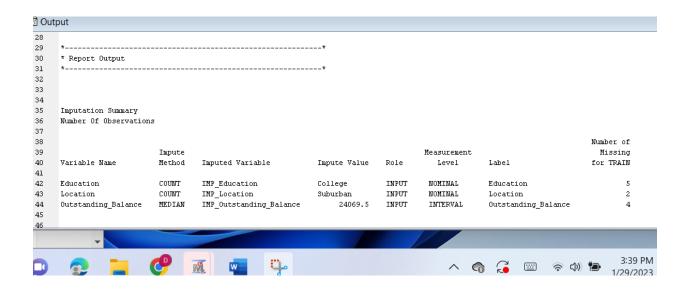
Missing Data

Missing values can cause the model result, which is why to improve data. Two methods to handle missing values; are listwise deletion and imputation, replacing the missing values with substitute values. The Impute node is used to deal with missing values. Click the Modify tab, then drag the Impute node to the process flow diagram. The Default Input Method for the Interval Variables changed from Mean to Median.



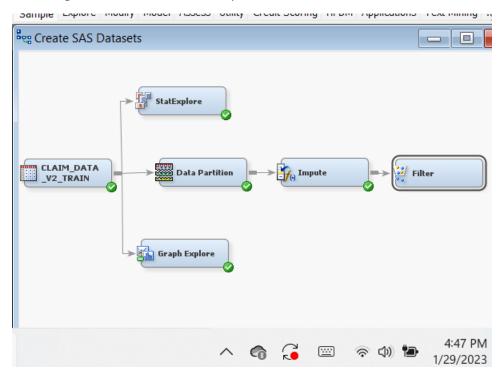


The Impute node creates a new table with a new variable replacement value for the missing data. The Impute node creates a default table as the original data set in the original dataset are not overwritten. New variables containing the impute values can identify with the prefix IMP_.



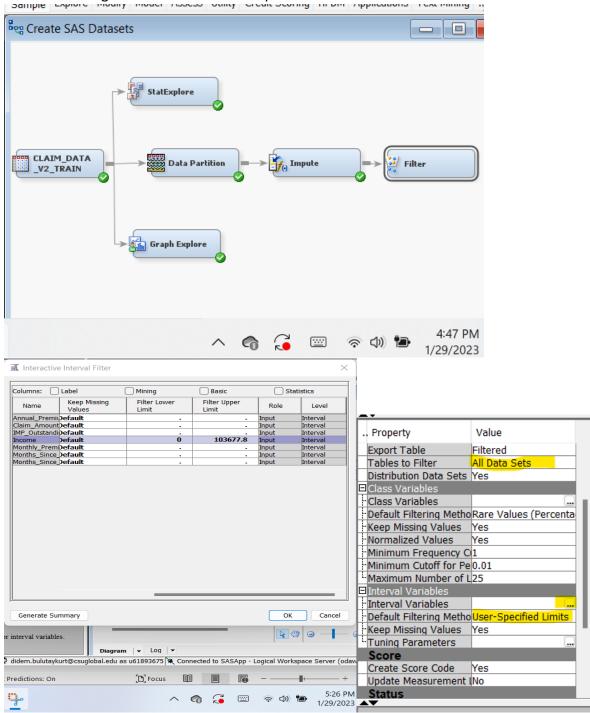
Handling Outliers

The Filter node helps to identify and eliminate outliers and filter the dataset. Filtering uses the data from the training dataset for the better result of models. Additionally, the Filter node ignores target and rejected variables. Use the Sample Tab, drag a Filter node to the process flow diagram, and connect the Impute to the Filter node.



Let's look at the Claim fraud dataset, as only Income has outliers on the Graph Explore node showed. Just the Income variable needs to be filtered; the filter setting needs to change under the Train group, Table to Filter set All Data Sets, and under the Interval Variables group, click

the Interval Variables' ellipsis and set the minimum income zero and the maximum income to 103,677.78 that value probably 99.7% of the values are within three standard deviations. The Default Filtering Method is set to User-Specified Limits.



🛅 Outp	out						
43							
44				Train	Train		Filter
45	Variable	Role	Level	Count	Percent	Label	Method
46	variable	1.010	20001	00410	10200110	I amer	110 0110 0
47	Claim Cause	INPUT	FIRE	1	0.033356	Claim_Cause	MINPCT
48	crarm_caasc	114101	1114	-	0.000000	crarm_caasc	HIMICI
49							
50							
51							
52	Number Of Obs						
53	Number of obs	ervacion	•				
54	Data						
55			F144	D.1773			
	Role F	iltered	Excluded	DATA			
56	TTD 1 T11						
57	TRAIN	2996	2	2998			
58	VALIDATE	2001	2	2003			
59							
60							
61							
62	Statistics for	_					
63	(maximum 500	observat	ions printed)				
64							
65	Data Role=TRA	IN Varia	ole=Income				
66							
67	Statistics		Original	Filtered			
68							
69	Non Missing		2998.00	2996.00			
70	Missing		0.00	0.00			
71	Minimum		0.00	0.00			
72	Maximum		933288.00	99981.00			
73	Mean		38326.89	38040.96			
74	Standard Devi	ation	34559.26	30448.93			
75	Skewness		5.97	0.28			
76	Kurtosis		148.50	-1.11			
77							
78							
79	Data Role=VAL	IDATE Va	riable=Income				
80							
81	Statistics		Original	Filtered			
82							
83	Non Missing		2003.00				
84	Missing		0.00	0.00			
85	Minimum		0.00	0.00			
86	Maximum		15967801.00	99960.00			
87	Mean		45776.10				
88	Standard Devi	ation	357290.69				
89	Skewness		44.25				
90	Kurtosis		1972.80	-1.09			
91							
92							
93	*					*	

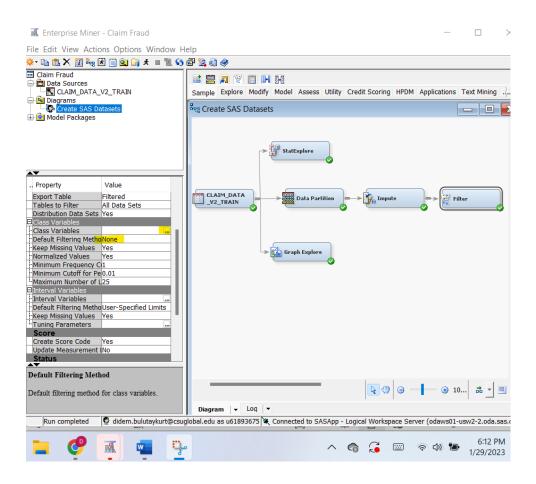
As a result, training and validation have two observations that were filtered. And the train data display that the maximum income value in the partition is \$99,981, but the original maximum value is \$933,288.

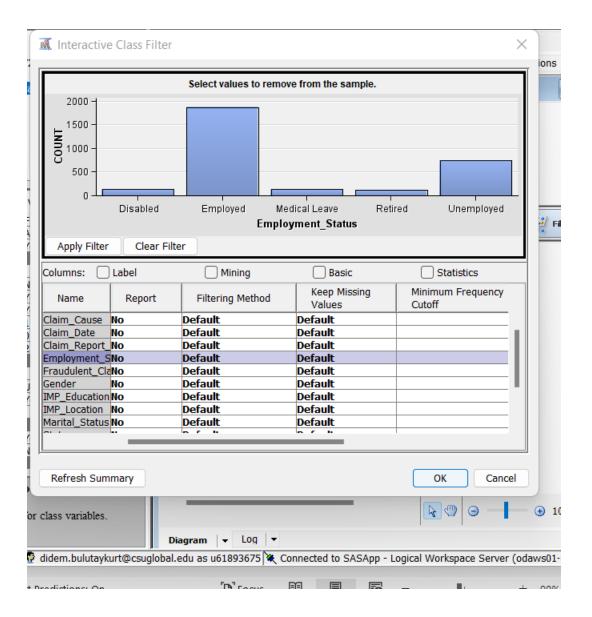
Categorical Variables with Too Many Levels

One of the practical uses of many categories or class variables, like zip code variables, is that they can be combined at the city or state levels and can also combine their frequency. The Replacement node connects groups and establishes different levels for the group. The Filter node can be used to set minimum frequency and several levels.

Use the same direction for the filter node, set None for the Default Filtering Method under the Class Variables group, and click on the ellipsis by Class Variables. And click on each variable to

see the histogram top on the window and can update the Minimum and Maximum Frequency Cutoff.





References

 $SAS\ Enterprise\ Miner\ by\ PAT\ RESEARCH,\ 2021.\ \underline{https://www.predictiveanalyticstoday.com/sas-particles}$

enterprise-miner/

Richard V. McCarthy; Mary M. McCarthy; Wendy Ceccucci, 2022. *Applying Predictive Analytics Finding Value in Data*. Second edition.