Descriptive Analytics with Claim Fraud Dataset/ SAS Enterprise Miner

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Descriptive Analytics

Descriptive analytics is the essential step of data analysis. This stage has a few critical topics; the summary measures of central tendency include the mean, median, and mode and historical data to understand better standard deviation, variance, range, and the kurtosis and skewness and prepare the data for predictive analytics. For example, if a variable is highly skewed, the variable may need to be normalized to produce a more accurate model.

Additionally, this project will touch on statistical correlation methods to develop and prepare the dataset for predictive models. Discuss the main topics with the Claim Fraud Dataset's summary statistics in the StatExplore node results Output Window.

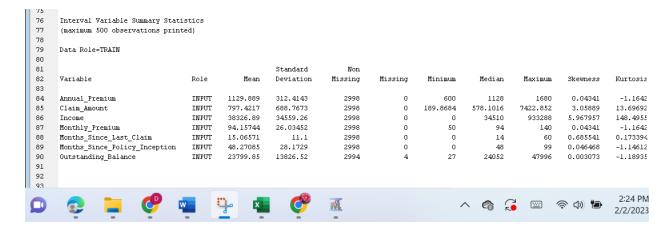


Figure 1: StatExplore Output Window- class variable summary statistics

Mean

The first thing to check the mean value is to see an average data point for each variable. Outliers and high values affect the mean values. For example, in the claim fraud dataset, 'Income' has the highest mean of \$30326.89, which shows the average income is a little high, and 'Annual_Prenium' has a higher value of 1129.889.

Median

The median is preferably measured at a distance from the mean if there are outliers or high variability in the dataset. The data is usually distributed if the mean and median length are small. Outliers and high values do not affect the median.



Figure 2: StatExplore Output Window- Class variable summary statistics

Mode

The mode is the most frequent data point that is rarely used, primarily as if categorical or class variables have missing values and can be replaced with mode values. The highest percentage of mode values for the 'Employement_Status' category 'Employed' at 62.61 and the 'Vehicle_Size' category 'midsize' at 70.05.

Variance and Distribution

The result of variance and distribution shows how data points spread that measure range differ between the minimum and maximum values. Outliers and high values affect the range. The most helpful measure is the sample variance, the average squared deviations of each observation from the mean.

Another standard deviation measure is the square root of the variance and is in the same units of measurement as the original data.

Figure 1 shows the summary statistics of the interval variables. The 'Claim_Amount' mean was \$797.4217, with a standard deviation of \$688.7673 and a median of \$578.1016.

We can see all the class variables with target variables by Train dataset; click View tab- Summary Statistics- Class Variables from the StatExplore Output Window.

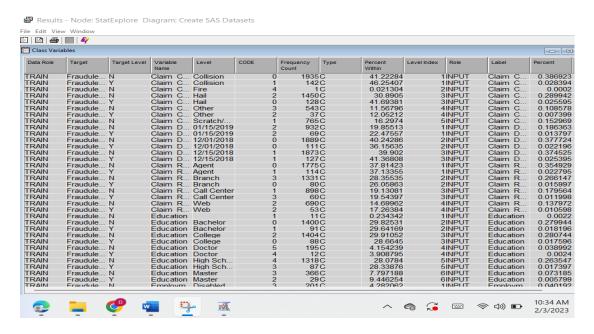


Figure 3: StatExplore node-class variable results

The class variable table shows a count of each class variable by target variable of Y or N as 2952 observations had an Employed for the 'Employemet_Status' variable and with no (N) 'Fraudulent_Claim' and 174 observations had an Employed level for the 'Employemet_Status' variable with yes (Y) 'Fraudulent_Claim.'

Skewness

Skewness tells that the dataset has an asymmetric distribution or is not symmetrical. There are three different distributions. One zero skew means the distribution is balanced (mean=median). Another negative skew is when the skewness value is negative (mean<median), and a positive skew is when the skewness value is positive(mean>median). For example, the skewness of temp shows a negative number of -0.33, which tells the left skew.

Figure 1 shows the average 'Annual_Prenium, 'Monthly_Prenium,' 'Months_Science_Last_Claim' and 'Months_Science_Policy_Inception" have close values for mean, and the median would have a normal distribution. 'Outstanding_Balance' has a left-skewed distribution. And 'Claim_Amount' and 'Income' have a right-skewed distribution.

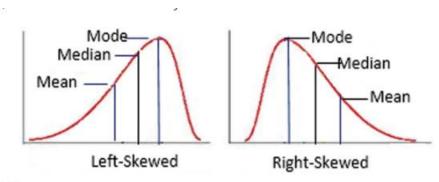


Fig. 3.10 Skewness

$$\frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} {x_i - \bar{x} \choose s} \qquad \text{Where n is the sample size,} \\ \frac{\mathsf{x_i} \text{ is the } \underline{\mathsf{j}}^\text{th} \text{ value of the variable,}}{\bar{x} \text{ is the sample average, and}} \\ \underline{\mathsf{s}} \text{ is the sample standard deviation}$$

Fig. 3.11 Skewness Formula

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

Kurtosis

Kurtosis shows the variable's probability or frequency, which also helps to compare which variable has a heavy distribution tail with three kurtosis types. I found so many different ranges people use. I want to use zero for the normal kurtosis distribution because I check outliers, and the best explanation for the

case outliers is the zero number for kurtosis. Medium tails are **mesokurtic(kurtosis=0)**, low kurtosis is **platykurtic(kurtosis<0)**, and high kurtosis is **leptokurtic(kurtosis>0)**.

Figure 1 shows the 'Moths_Scince_Last_Claim' kurtosis value was 0.05, close to the zero would be mesokurtic, and the 'Income' kurtosis of 4790, which is pretty high, is leptokurtic.

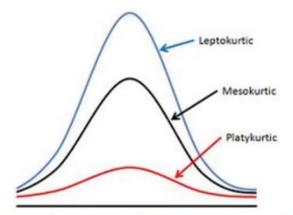


Fig. 3.12 Kurtosis taken from https://www.bogleheads.org/wiki/Excess_kurtosis

$$\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^{n} \left(\frac{(x_i - \overline{X})}{S} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Where n is the sample size, x_i is the i_i^{th} value of the variable, \bar{x} is the sample average, and x_i^{th} is the sample standard deviation

Fig. 3.13 Kurtosis formula

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

The best way to solve skewness and kurtosis problems with transformations is when there is a relatively wide range of values instead of a relatively small range. The log transformation transforms skewed data to follow an approximately normal distribution. "For the variable claim_amount, the skewness value was 2.922 and kurtosis 12.62. Notice that the skewness and kurtosis values for income were \$68.48667 and \$4790.542, respectively. Income is highly right-

skewed with a leptokurtic shape. Income should be transformed to provide a more accurate model. The Transform node can be used to modify the income variable. "(McCarthy,2022) Click the Modify tab, drag and drop Transform Variables on the process diagram, and connect the Filter node.

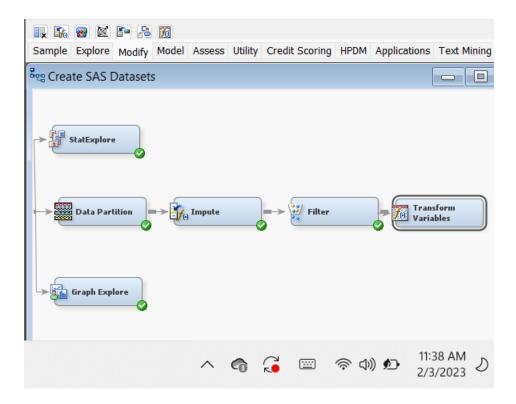


Figure 4: Transform Variables node

The left side has a Transform Properties window; click to ellipse Formulas on the Train group.

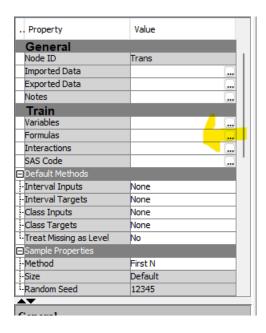


Figure 5: Transform Variables properties

Then, a new window will pop up, and you can choose any variable to see the histogram; the income variable has a right-skewed.

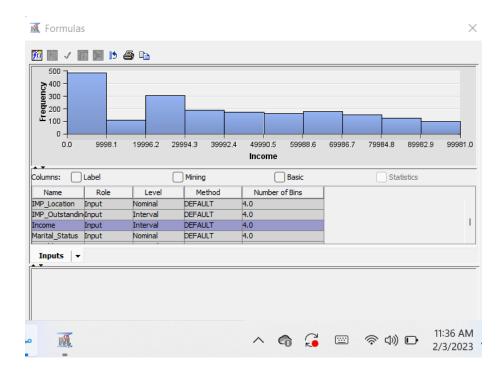


Figure 6: Formulas window- Income distribution

Click the ellipse button on the Train group's Variable; a new Variables-Trans window will open and change the method from Default to Log for the Income variable. Next, we should update the Transform Properties window, set the Default Methods for Interval Inputs to None, and Run the Transform Variables node.

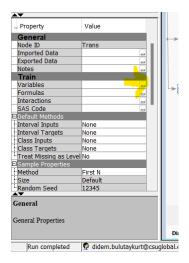


Figure 7: Transform Properties Window

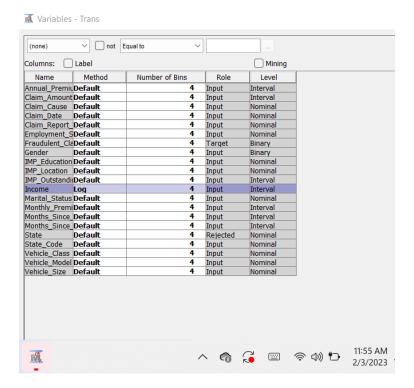


Figure 8: Transform Variables window.

The result of the Transform node is that the Income skew ness value is close to zero now that Income is a normal distribution variable.

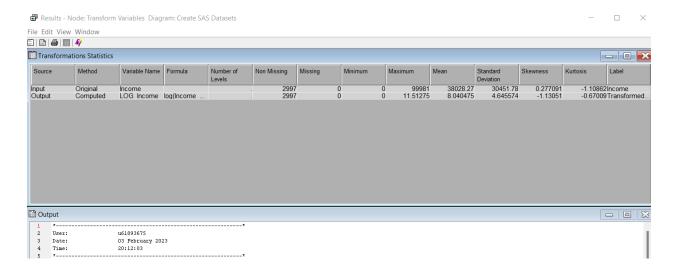


Figure 9: Results of Transform node

Covariance and Correlation

The covariance measures two variables, x (input, independent variable) and y (target, dependent variable), so the correlation (r) ranges from -1 to +1. If the covariance is more significant than zero, a positive relation means two variables move in the same direction; with less than zero negative relation, two variables move in the opposite direction with equal zero X and Y nonrelation independent. "The covariance value is the product of the two variables and is not a standardized unit of measurement. So, measuring the degree to which the variables move together is impossible." (McCarthy, 2022)

The square correlation (r^2) or the coefficient of determination measures the percent of the variation in the target variable by the input variable. The R-square range is 0% to 100%. Mostly, use the scatter plot chart to see the plot of the two variables.

If two variables have a strong correlation, there should be some multicollinearity that negatively affects the predictive model. We can solve this problem with SAS Enterprise Miner; click the Explore tab, drag and drop the Variable Cluster node on the diagram, and Run. See the Result table; click View tab-Model- Variable Correlation, then pop up the Variable Correlation window. There is a tab icon showing the list. Again, there is no collinearity to warrant concern.

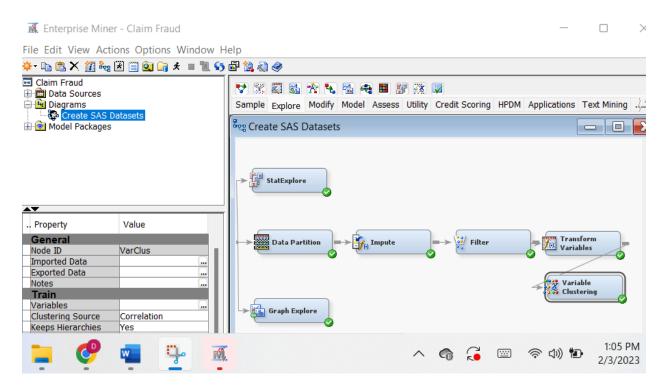


Figure 10: Variable Cluster node

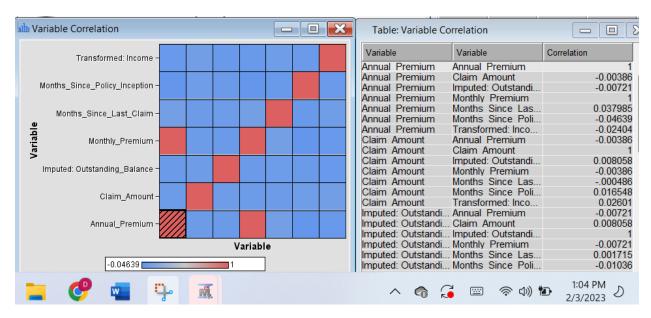


Figure 10: Variable correlation matrix and table result- Variable Cluster

Variable Reduction

This is the excellent part I read because when completed claim fraud data hadn't multicollinearity, I asked if had how to solve it. That part answered my question. If the dataset has multicollinearity or more variables, reducing the number of variables can decrease multicollinearity, redundancy, and

irrelevancy and improve the model result. Variable Clustering and Principal Component analysis solve the multicollinearity problem.

Variable Clustering

Variable clustering measures the correlations and covariances between the input variables and creates close data point groups or similar variables. The main aim is to reduce the correlation within the groups.

Points (4,8) and (5,6) are the closest, so they are combined to form cluster 2. The centroid for cluster 2 is (4.5, 7) (Fig. 3.33).

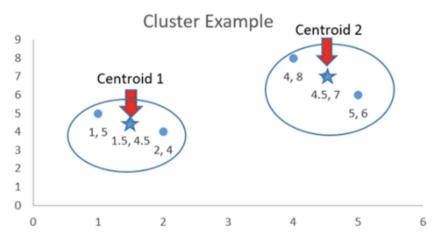


Fig. 3.33 Scatter plot with two clusters

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

Figure 3.33 shows two clusters as a question of when to stop the combining clusters. This might be a reason to pre-define the number of clusters or set the max distance between the group and the points.

The Variable Cluster node in SAS Enterprise Miner can create different clusters and select the representative variables from the cluster. If the dataset has more than 30 variables, the Train group should be set to Yes on the Keep Hierarchies, and Two Stage Clustering should be set to Yes. This method for identifying the variables passed to the subsequent node will filter the best variables in each cluster with the min r-square ratio value. Two-stage variable clustering should be used if the dataset has more than 100 variables and more than 100,00 observations.

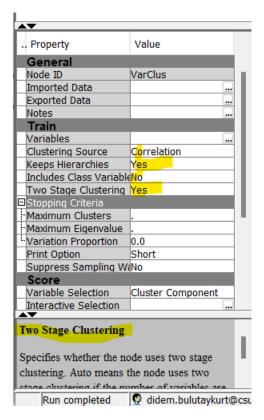


Figure 11: Variable Cluster node properties for more than 30 variables.

The Cluster Plot results from the Variable Cluster node show the objects' hierarchical relationship. The diagram read left to right; a long line means a more significant difference. The relationship between the LOG_INCOME and CLAIM_AMOUNT, MONTHLY_PREMIUM, and MONTHLY_SINCE_POLICY_INCEPT, and ANNUAL_PREMIUM are most similar and are first joined together. IMP_OUTSTANDING_BALANCE and MOUNTHLY_SINCE_LAST_CLAIM are connected to the cluster, meaning the variables more like each other than any variable or cluster joins at a significant level.

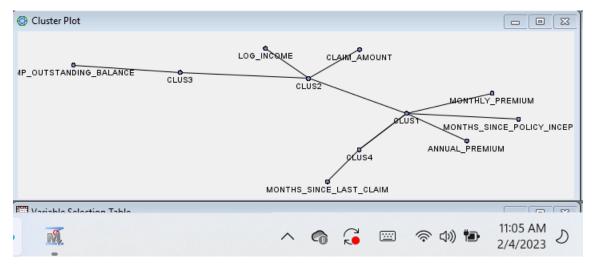


Figure 12: Claim Fraud cluster plot

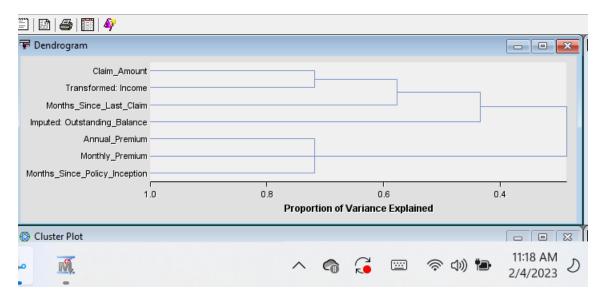


Figure 13: Claim Fraud dataset dendrogram

Principal Component Analysis

This is another variable reduction strategy. It is used when several redundant variables or variables correlate with one another and may measure the same construct. Principal component analysis mathematically manipulates the input variables and develops fewer artificial variables.

Drag and drop The Principal Components node to the diagram work area on the Modify tab. The node result shows a scatter plot and Eigenvalue to see the relation. "The plot shows the Eigenvalues on the y-axis and the number of principal components on the x-axis. It will always be a downward curve; the point where the slope of the curve flattens indicates the number of principal components needed. "(McCarthy, 2022)

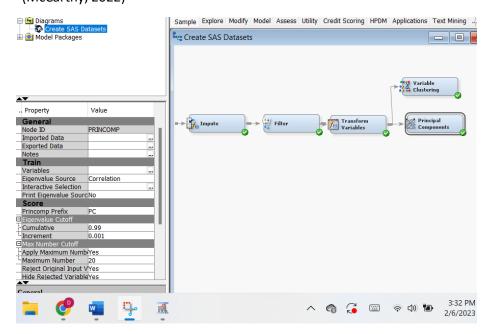


Figure 14: Principal Component node properties

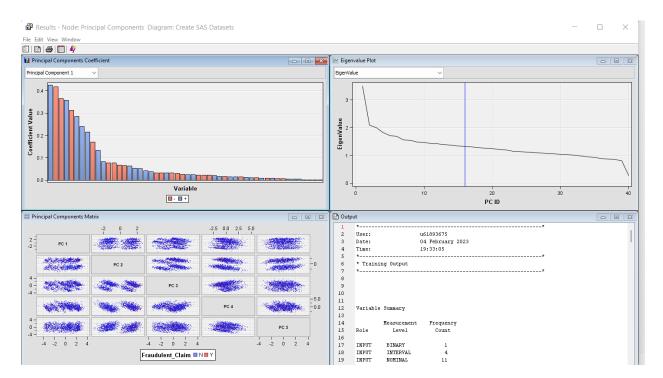


Figure 15: Principal Component node result.

Hypothesis Testing and Chi-Square

The hypothesis testing helps to create business questions with null hypothesis Ho should be tested, and alternative hypothesis AH_A is opposite of the null hypothesis. There are two types of errors; a type I error refers to alpha as the significant level. If the p-value is smaller or equal to alpha 0.05, reject the null hypothesis and accept the alternative hypothesis. Do not reject the null hypothesis if the p-value is higher or equal to a significant level.

Ho: Gender and claim fraud are independent.

 H_A : Gender and claim fraud are not independent.

The Chi-Square test determines if there is a significant relation between two categorical variables. In the SAS Enterprise Miner, drag and drop StatExplorer in the Model tab on diagrams workplace and set the Interval Variables in the Chi-Square Statistic group Yes. Figure 17 shows the output of the gender p-value at .000, lower than 0.05, which means rejecting the null hypothesis.

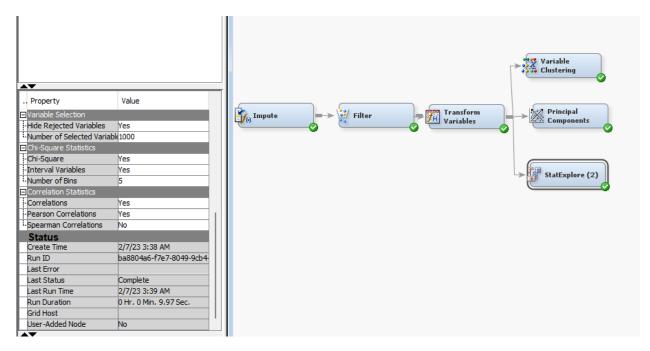


Figure 16: StatExplore node for Chi-Square test in Explore tab.

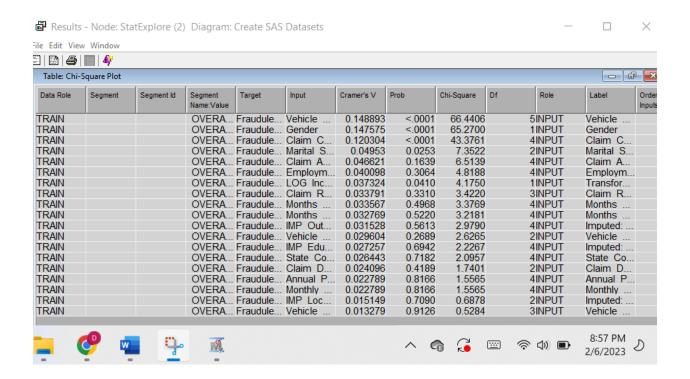


Figure 17: Chi-Square Plot window output.

Reference

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

Farhad Malik, 2019. Is there A Statistical Method To Test A Claim? https://medium.com/fintechexplained/is-there-a-statistical-method-to-test-a-claim-8d847adabd81