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Easily Turn Your Automated Explanation into a Predictive Model

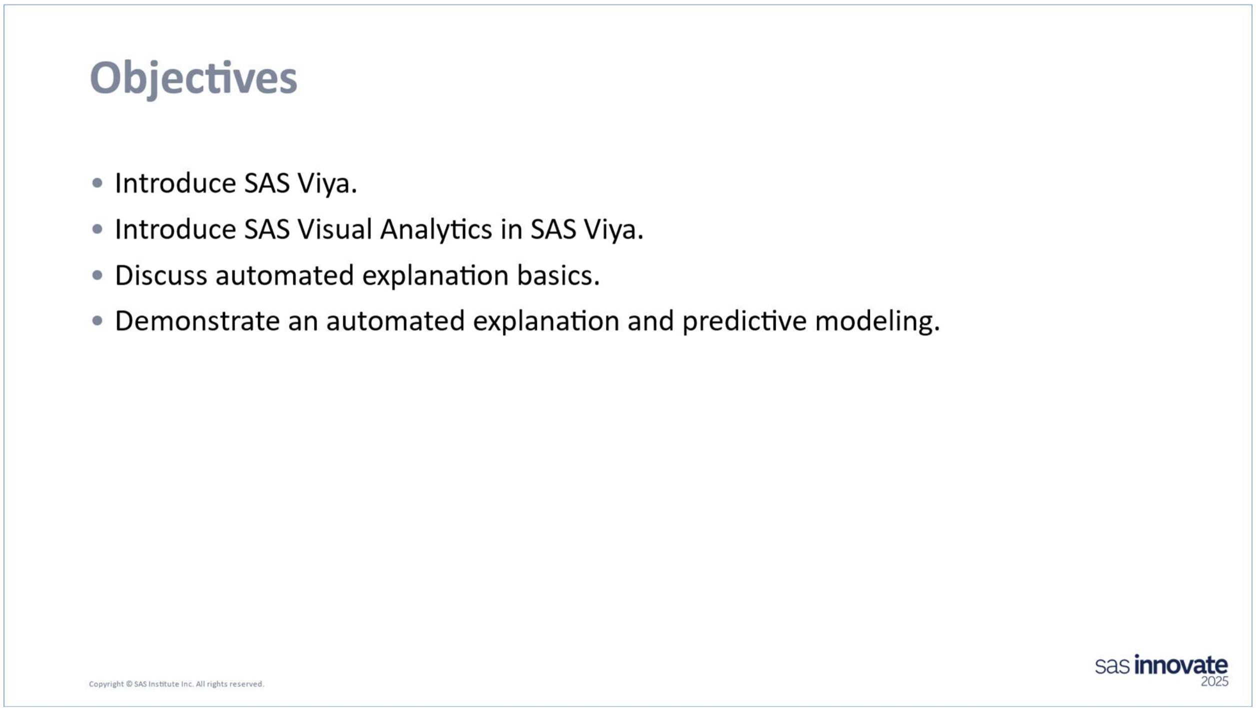
Danny Modlin

Andy Ravenna

#SASinnovate

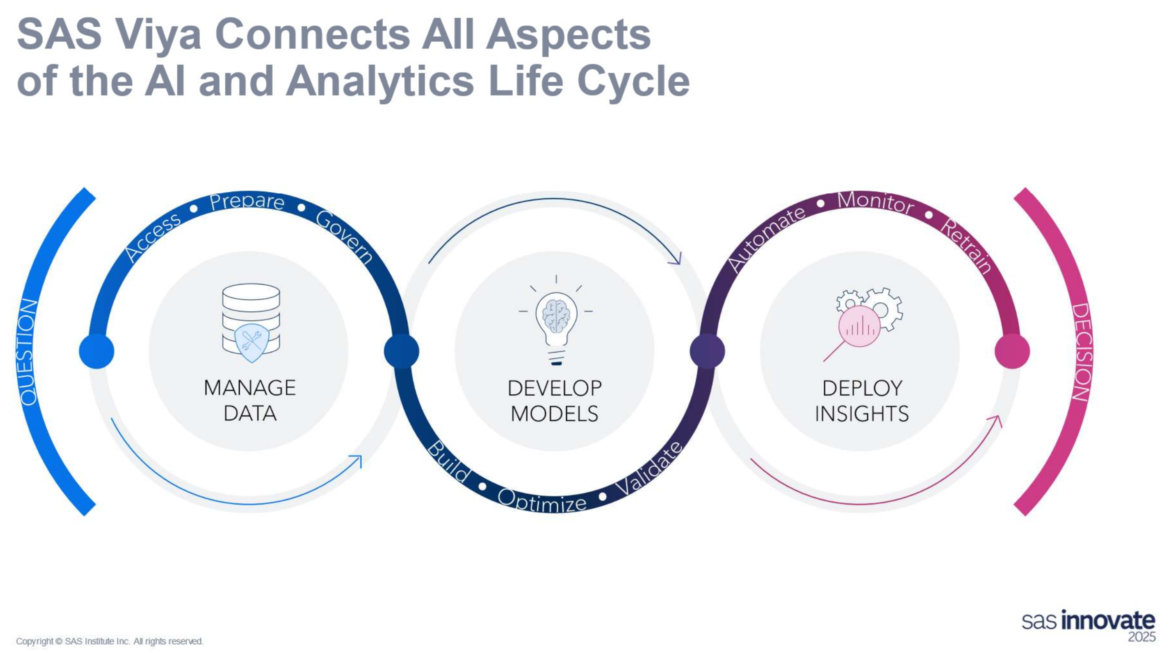
Lesson 1 Easily Turn Your Automated Explanation into a Predictive Model

1.1 Introduction



Objectives

- Introduce SAS Viya.
- Introduce SAS Visual Analytics in SAS Viya.
- Discuss automated explanation basics.
- Demonstrate an automated explanation and predictive modeling.



SAS Viya Connects All Aspects of the AI and Analytics Life Cycle

QUESTION
Access • Prepare • Govern
MANAGE DATA
DEVELOP MODELS
Build • Optimize • Validate
Automate • Monitor • Retrain
DEPLOY INSIGHTS
DECISION
sas innovate 2025

SAS Viya is a cloud-enabled, in-memory analytics engine that provides quick, accurate, and reliable analytical insights. In SAS Viya, the SAS High-Performance Architecture enables the high-performance analytics engine. The CAS In-Memory Engine continues the ability to perform processing in memory and the ability to distribute processing across nodes in a cluster. The CAS In-Memory Engine adds highly efficient node-to-node communication and uses an algorithm to determine the optimal number of nodes for a given job.

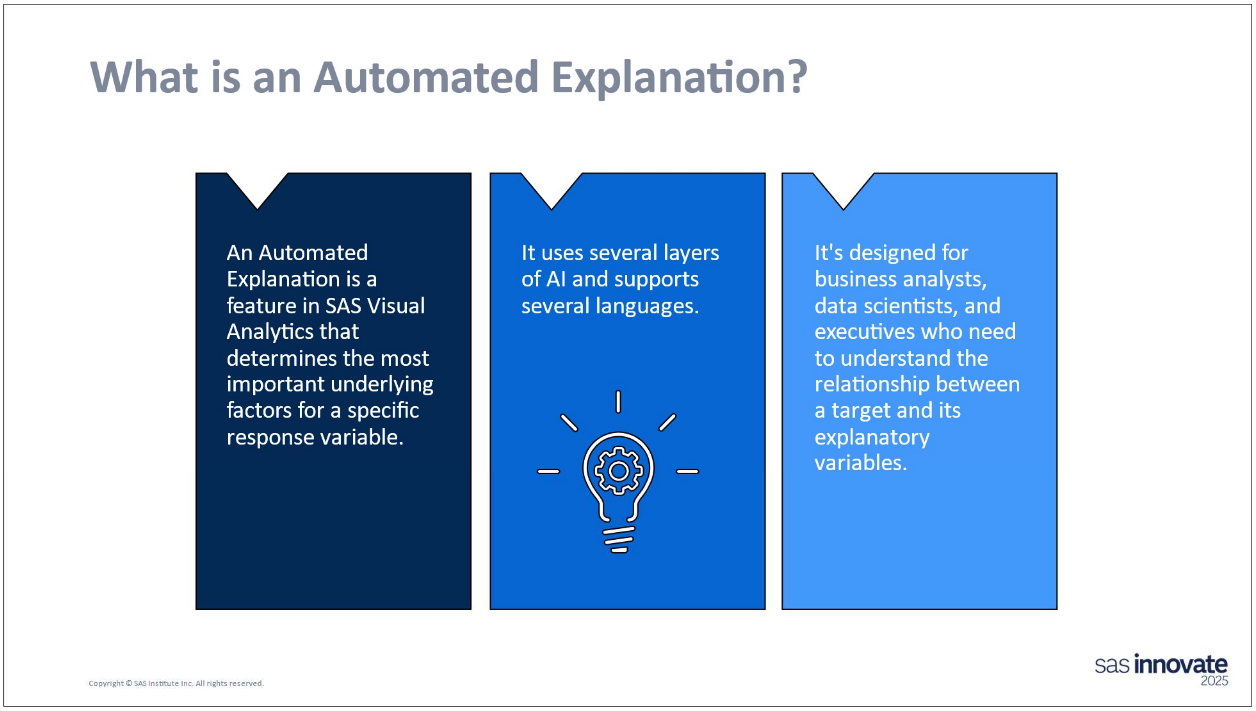
SAS Cloud Analytic Services, or CAS, is a server that provides the cloud-based run-time environment for data management and analytics with SAS. By *run-time environment*, we refer to the combination of hardware and software where data management and analytics take place.

The server can run on a single machine or as a distributed server on multiple machines. The distributed server consists of one controller and one or more workers. This architecture is often referred to as a *massively parallel processing architecture*. For both modes, the server is multi-threaded for high-performance analytics.

The distributed server has a communication layer that supports fault tolerance. A distributed server can continue processing requests even after losing connectivity to some nodes. The communication layer also enables you to remove or add nodes from a server while it is running.

One of the design principles of the server is to handle large problems and to work with tables that exceed the memory capacity of the environment. In order to address this principle, data in the server is managed in blocks. Whenever needed, the server caches the blocks on disk. It is this feature that enables the server to manage memory efficiently, handle large data volumes, and remain responsive to requests.

You can use a variety of interfaces to interact with the CAS In-Memory Engine. These interfaces include SAS Studio, which is a browser-based interface for writing SAS code. You can also use programming interfaces for R, Python, Java, and Lua to access this CAS functionality. In addition, you can continue to submit SAS code in batch mode.



What is an Automated Explanation?

An Automated Explanation is a feature in SAS Visual Analytics that determines the most important underlying factors for a specific response variable.

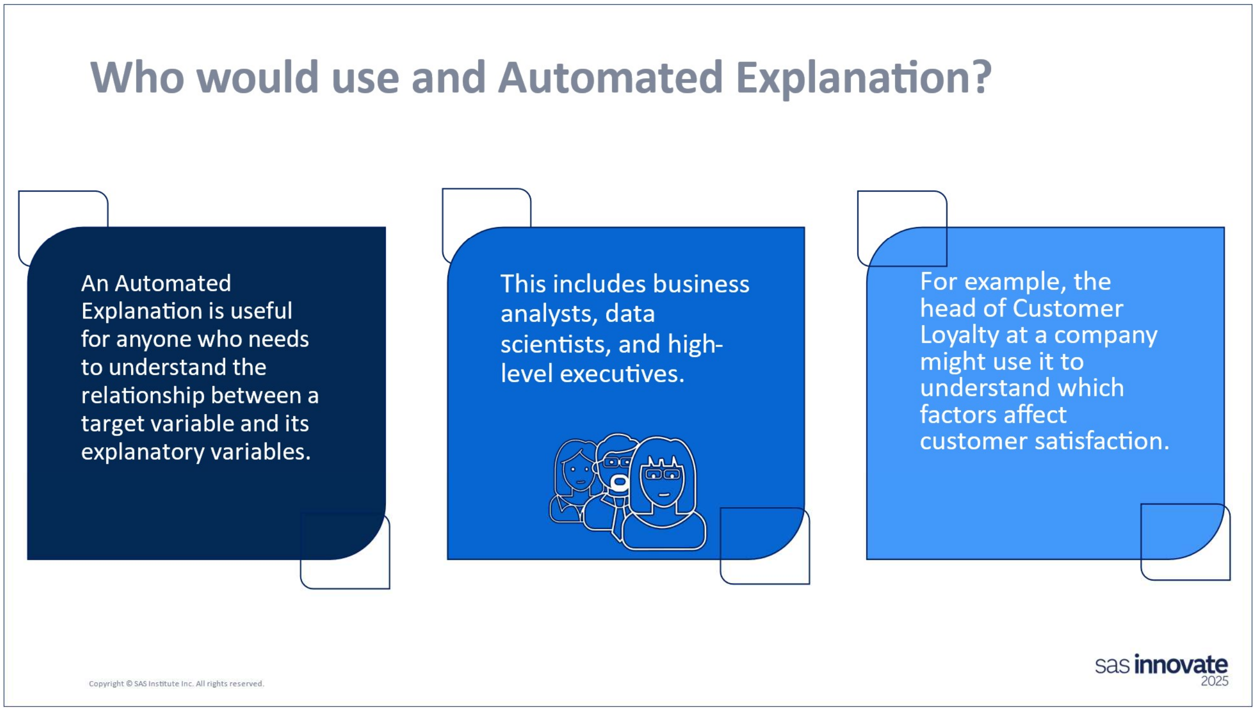
It uses several layers of AI and supports several languages.

It's designed for business analysts, data scientists, and executives who need to understand the relationship between a target and its explanatory variables.

Visual Analytics uses SAS High-Performance technologies to accelerate analytic computations, which helps you derive value from massive amounts of data. This gives you the power to solve difficult problems, improve business performance, predict future performance, and mitigate risk rapidly and confidently. You can import data of any size into Visual Analytics to quickly identify trends and patterns that you might not have noticed before.

Then, you can take your analysis a step further by creating powerful statistical models on the patterns that you discovered (with SAS Visual Statistics). After you identify those patterns and get a better feel for your data, you can create reports or dashboards to share with anyone, anywhere via the web or a mobile device.

SAS Visual Analytics helps you to visualize and discover relevant relationships in your data. You can create and share interactive reports and dashboards and use self-service analytics to quickly assess probable outcomes for smarter, more data-driven decisions.



Who would use and Automated Explanation?

An Automated Explanation is useful for anyone who needs to understand the relationship between a target variable and its explanatory variables.

This includes business analysts, data scientists, and high-level executives.

For example, the head of Customer Loyalty at a company might use it to understand which factors affect customer satisfaction.

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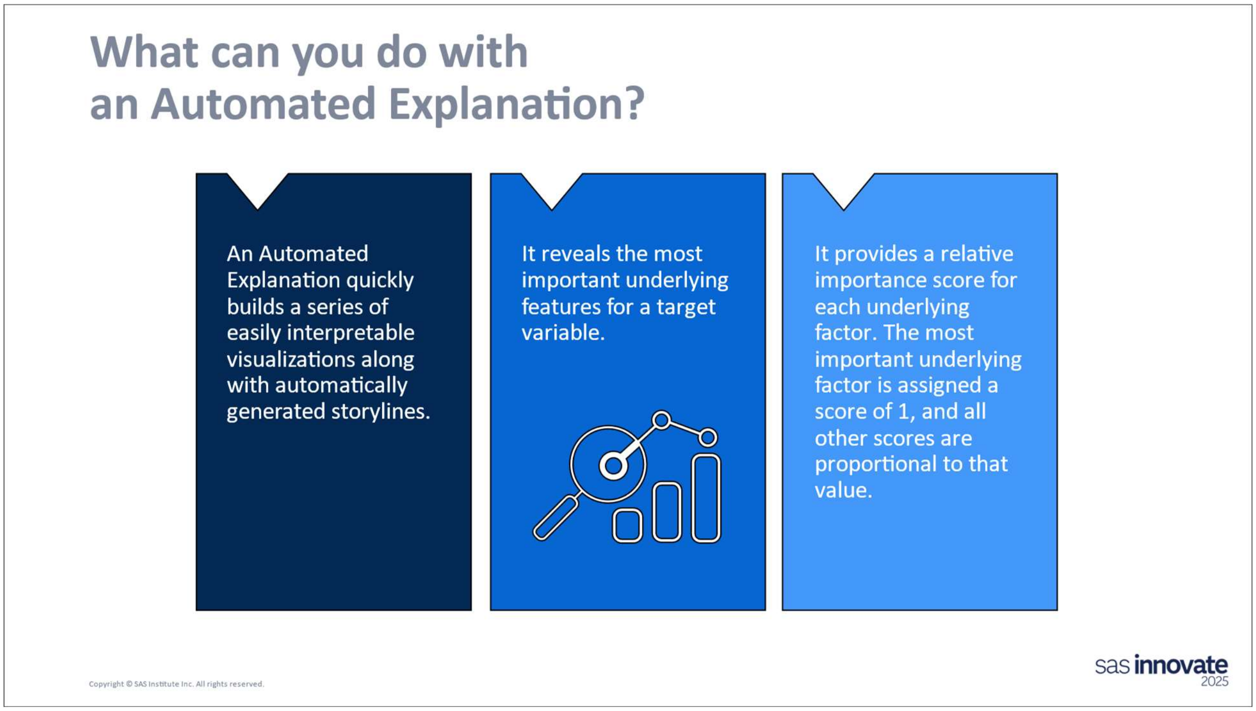
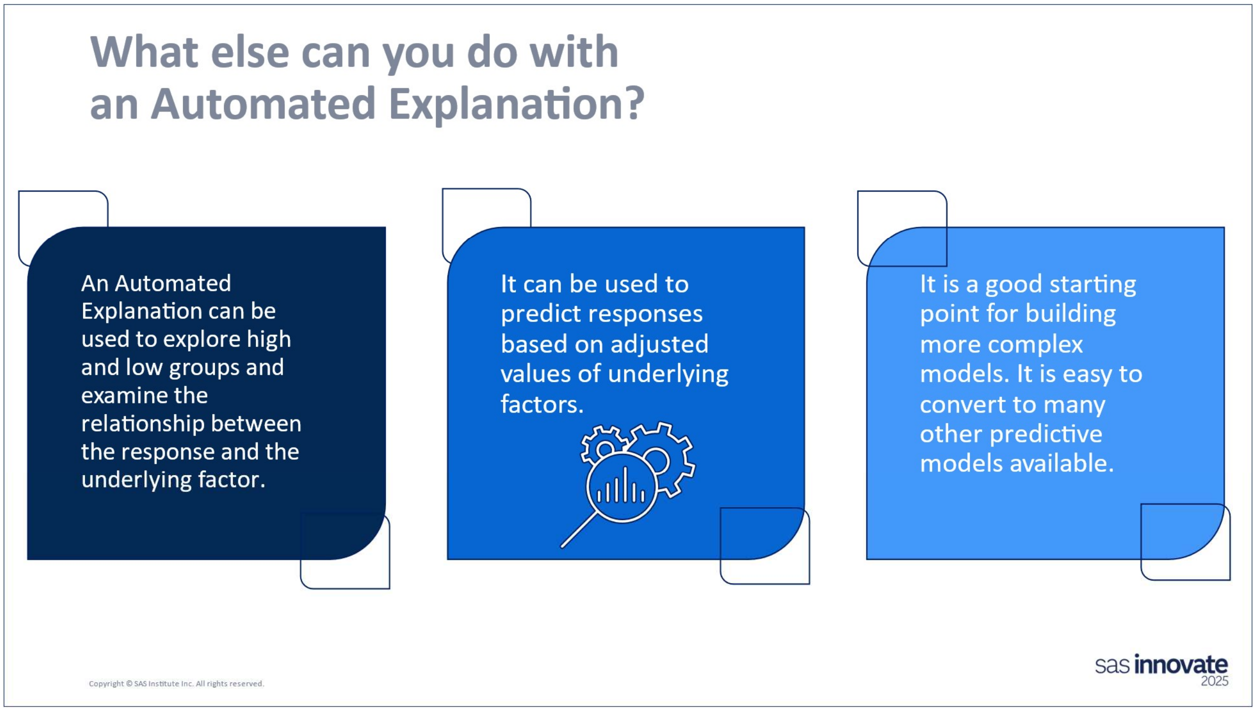


What can you do with an Automated Explanation?

An Automated Explanation quickly builds a series of easily interpretable visualizations along with automatically generated storylines.

It reveals the most important underlying features for a target variable.

It provides a relative importance score for each underlying factor. The most important underlying factor is assigned a score of 1, and all other scores are proportional to that value.



What else can you do with an Automated Explanation?

An Automated Explanation can be used to explore high and low groups and examine the relationship between the response and the underlying factor.

It can be used to predict responses based on adjusted values of underlying factors.

It is a good starting point for building more complex models. It is easy to convert to many other predictive models available.

1.2 Hands-On Workshop

In this workshop, you use the data set **vs_bank**. This data set consists of observations taken from account holders at a large financial services firm. The accounts represent consumers of home equity lines of credit, automobile loans, and other short- to medium-term credit instruments. Appropriate data cleansing has already been applied, so we can begin with statistical modeling. The target variables relate to whether that account holder purchased a new product from the bank in the past year. The data sets contain more than 1 million rows and 24 columns. A list of variables and their labels is shown below.

Target Variable

B_TGT	New Product (Binary)

Categorical Inputs

CAT_INPUT1	Account Activity Level
CAT_INPUT2	Customer Value Level

Interval Inputs

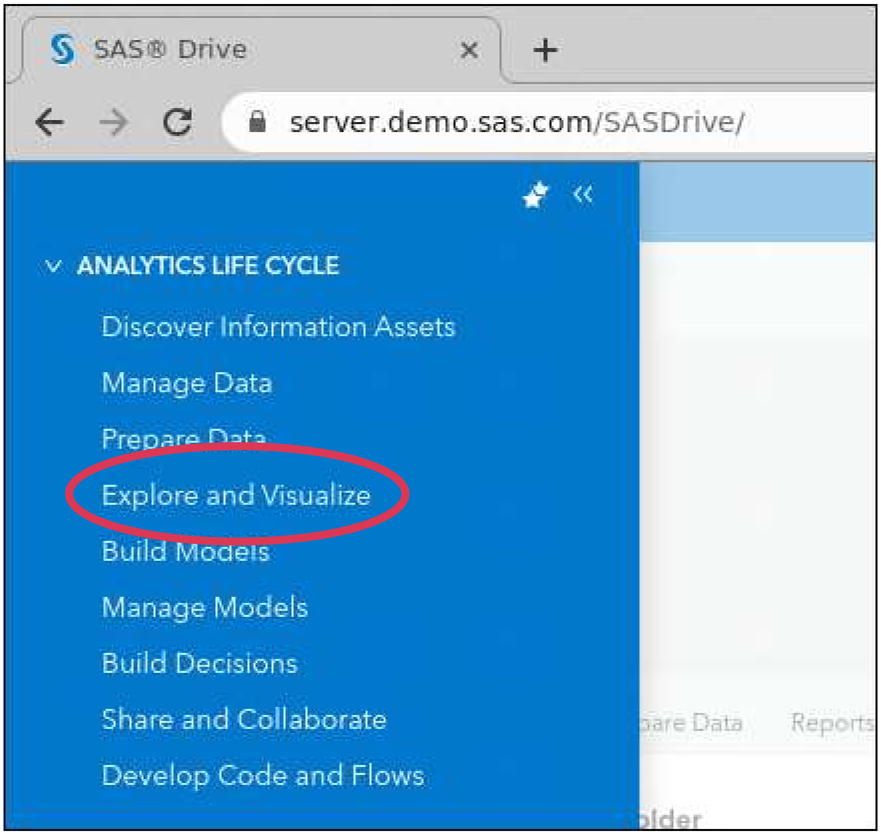
RFM1	Average Sales Past Three Years
RFM2	Average Sales Lifetime
RFM3	Avg Sales Past Three Years Dir Promo Resp
RFM4	Last Product Purchase Amount
RFM5	Count Purchased Past Three Years
RFM6	Count Purchased Lifetime
RFM7	Count Prchsd Past Three Years Dir Promo Resp
RFM8	Count Prchsd Lifetime Dir Promo Resp
RFM9	Months Since Last Purchase
RFM10	Count Total Promos Past Year
RFM11	Count Direct Promos Past Year
RFM12	Customer Tenure

Note: Other variables, not listed here, are also included in the data set. Variables with the prefix **I_** are imputed. Variables with the prefix **RI_** are imputed and replaced. Variables with the prefix **LOGI_** are imputed and log transformed. Variables with the prefix **DEMOG_** are demographic inputs.

Building a Logistic Regression Model

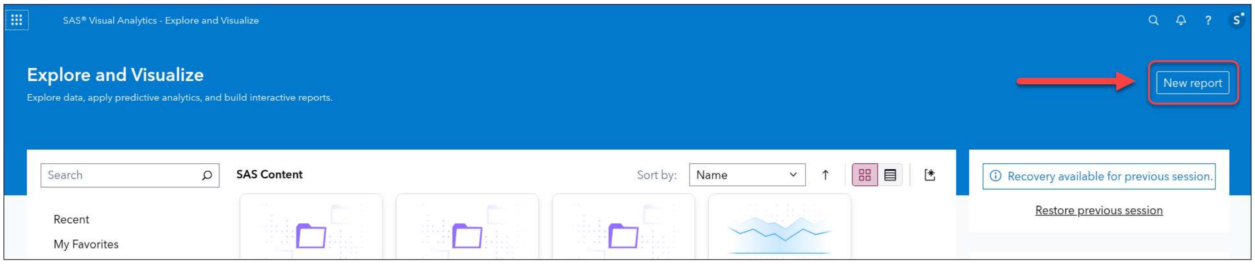
This demonstration illustrates how to build a logistic regression model in SAS Visual Analytics. The demonstration uses the **vs_bank** data to model whether a customer contracted for at least one product in the previous campaign season. You create a binary logistic regression with both categorical and continuous explanatory variables. You then perform model validation and variable selection.

1. From the desktop, open Google Chrome.
2. From the Google Chrome toolbar, select **SAS Drive**.
3. Enter **student** in the **User ID** field, if necessary.
4. Enter **Metadata0** in the **Password** field, if necessary.
5. Select **Sign in**.
6. If requested to save the password, select **Save**.
7. Select **YES** when asked about assumable groups.
8. Access the applications menu in the upper left of the window and select **Explore and Visualize**.

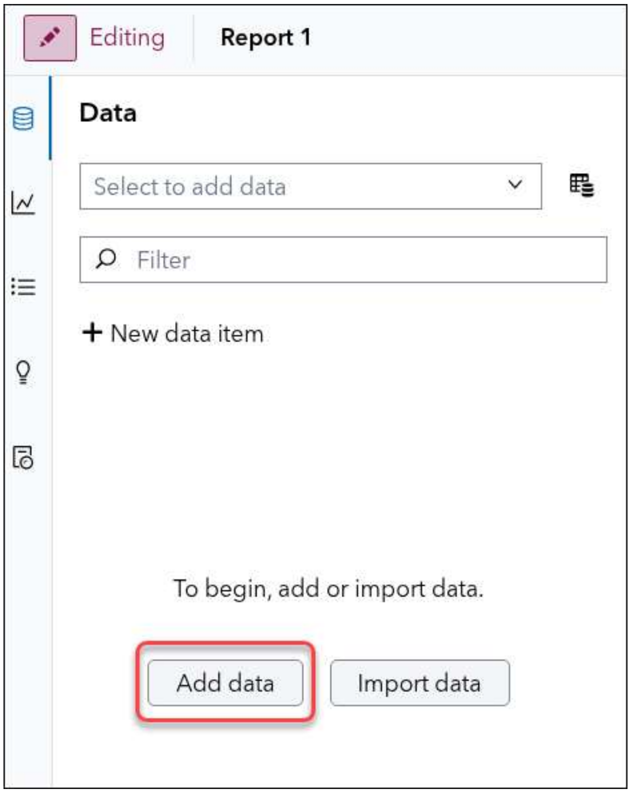


9. Load the SAS data set into CAS.

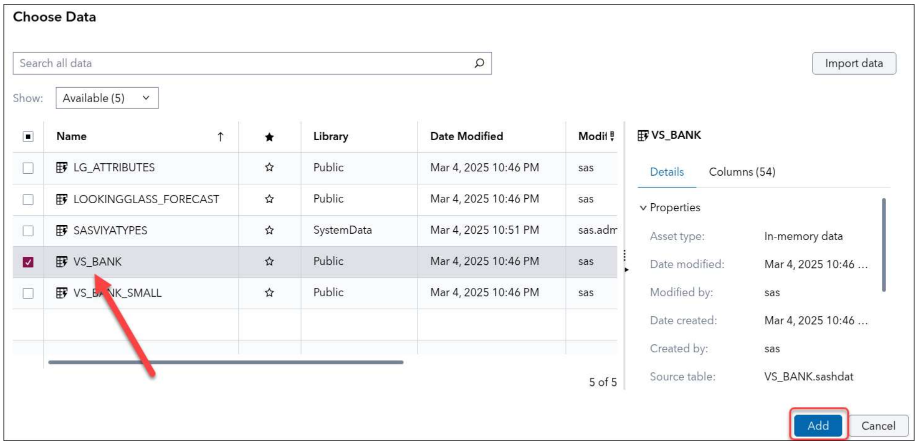
   a. In the Explore and Visualize window, click **New report**.


SAS® Visual Analytics - Explore and Visualize
Explore and Visualize
Explore data, apply predictive analytics, and build interactive reports.
New report
Search
SAS Content
Sort by:
Name
Recent
My Favorites
Recovery available for previous session.
Restore previous session

   a. On the Data tab on the left of the screen, select **Add data** to load an in-memory table to SAS Visual Analytics.



b. In the Choose Data window, select **VS_Bank > Add**.



☐	Name	★	Library	Date Modified	Modi
☐	LG_ATTRIBUTES	☆	Public	Mar 4, 2025 10:46 PM	sas
☐	LOOKINGGLASS_FORECAST	☆	Public	Mar 4, 2025 10:46 PM	sas
☐	SASVIYATYPES	☆	SystemData	Mar 4, 2025 10:51 PM	sas.adm
☑	VS_BANK	☆	Public	Mar 4, 2025 10:46 PM	sas
☐	VS_BANK_SMALL	☆	Public	Mar 4, 2025 10:46 PM	sas

VS_BANK

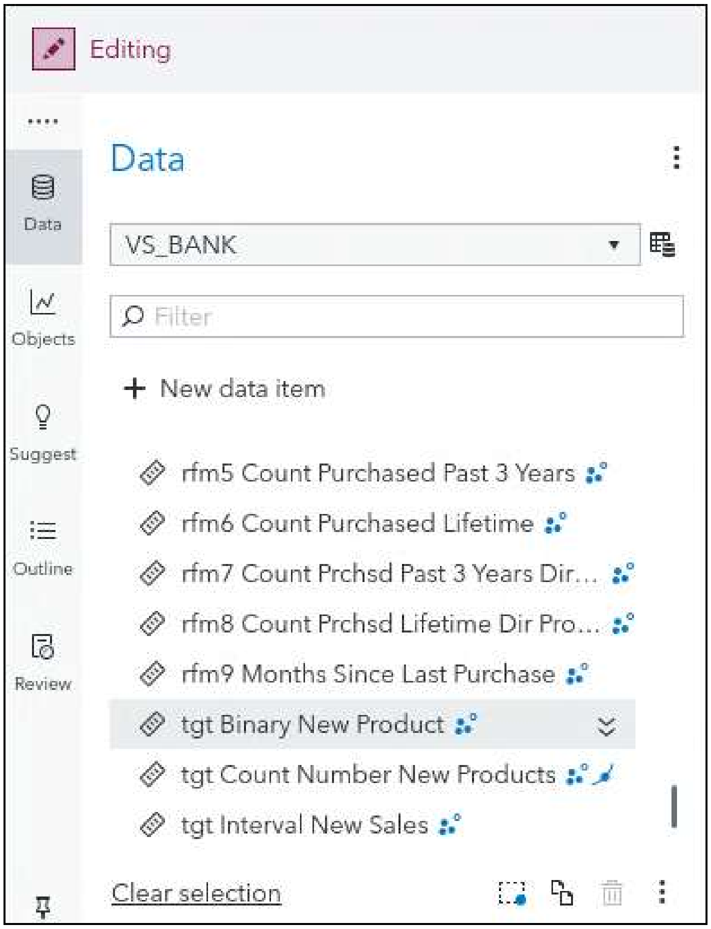
Properties

Asset type:	In-memory data
Date modified:	Mar 4, 2025 10:46 ...
Modified by:	sas
Date created:	Mar 4, 2025 10:46 ...
Created by:	sas
Source table:	VS_BANK.sashdat

c. The table is now available to the newly created report.

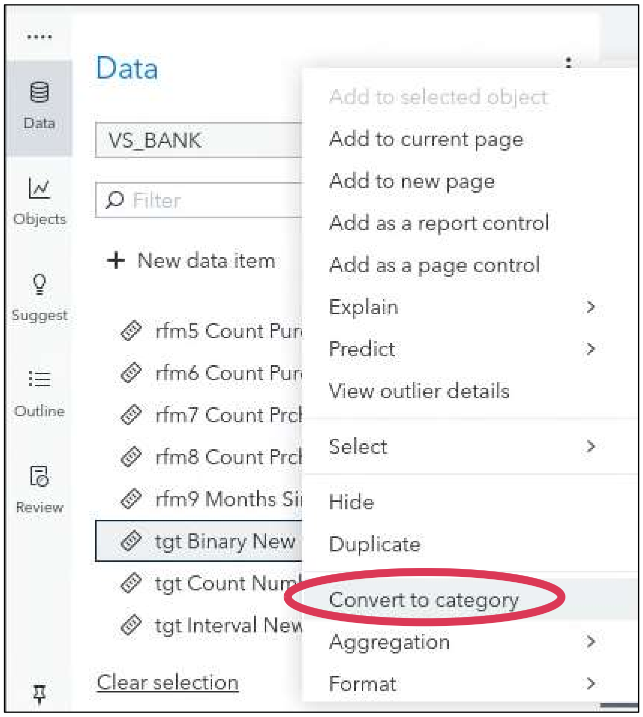
10. On the Data tab on the left of the screen, scroll down and find the measure **tgt Binary New Product**.

    The variable **tgt Binary New Product** (**b_tgt**) is the primary dependent variable for categorical response modeling in this workshop. It is a binary flag that codes responders with 1 and non-responders with 0. Because it is numeric, it is treated as interval valued by default.

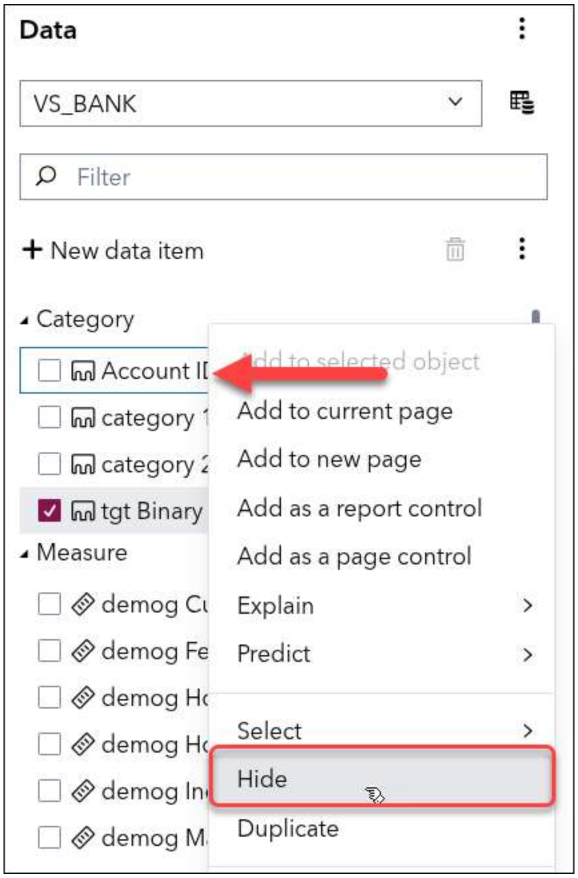


- rfm5 Count Purchased Past 3 Years
- rfm6 Count Purchased Lifetime
- rfm7 Count Prchsd Past 3 Years Dir…
- rfm8 Count Prchsd Lifetime Dir Pro…
- rfm9 Months Since Last Purchase
- tgt Binary New Product
- tgt Count Number New Products
- tgt Interval New Sales

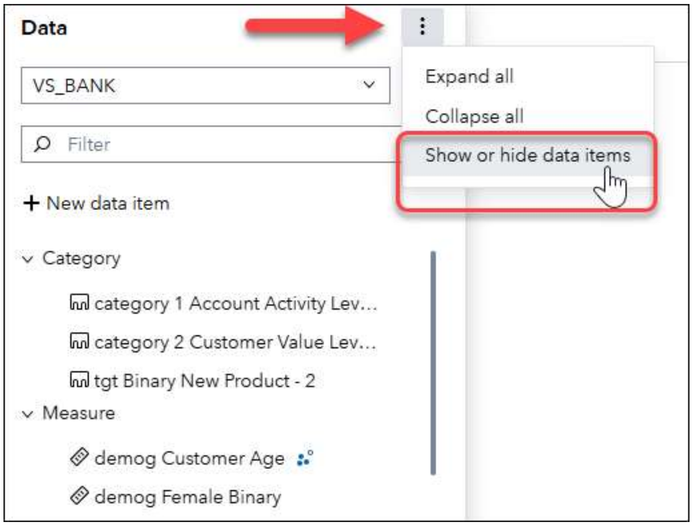
11. Right-click **tgt Binary New Product** and select **Convert to category**.



12. We need to hide several inputs so that they will not be included in our automated explanation. We will start by hiding the account id. Right-click **Account ID** and select **Hide**.

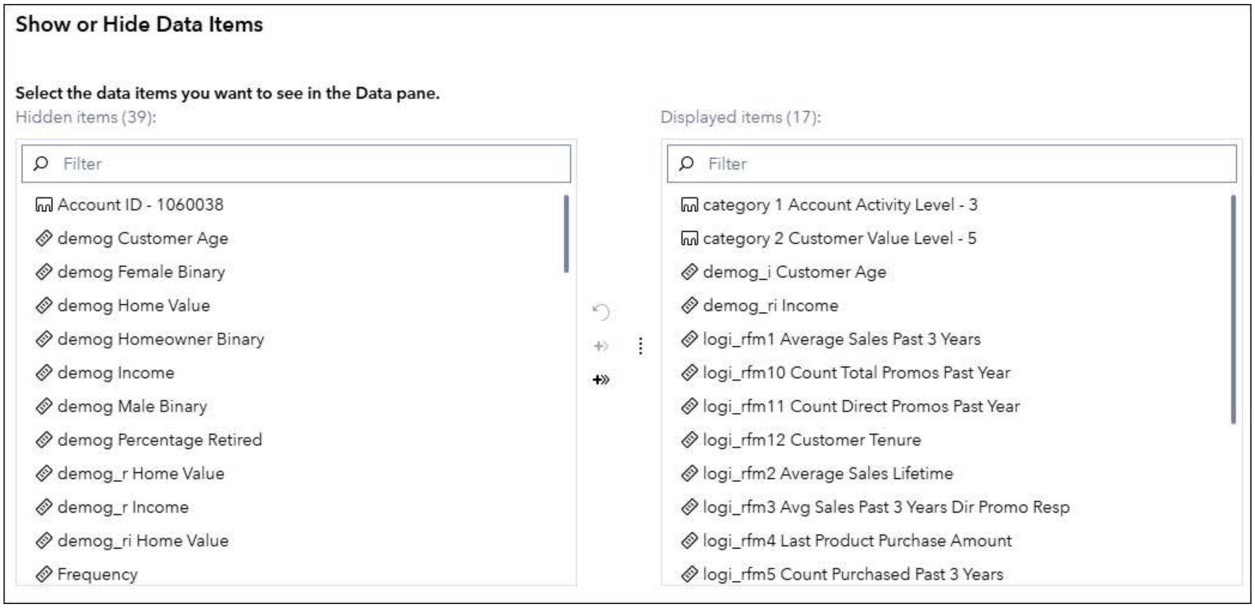


13. Next we will hide several variables at one time. Select **Data menu > Show or hide data items**.



14. In the Show or Hide Data Items window, move all the measures over to the hidden items column except for:
    a. demog_i Customer Age
    b. demog_ri income
    c. all logi_ variables

    Important Note: Do **not** move the 2 remaining categorical variables to be hidden. Do **not** move the target variable to be hidden.



Show or Hide Data Items

Select the data items you want to see in the Data pane.

Hidden items (39):

- Account ID - 1060038
- demog Customer Age
- demog Female Binary
- demog Home Value
- demog Homeowner Binary
- demog Income
- demog Male Binary
- demog Percentage Retired
- demog_r Home Value
- demog_r Income
- demog_ri Home Value
- Frequency

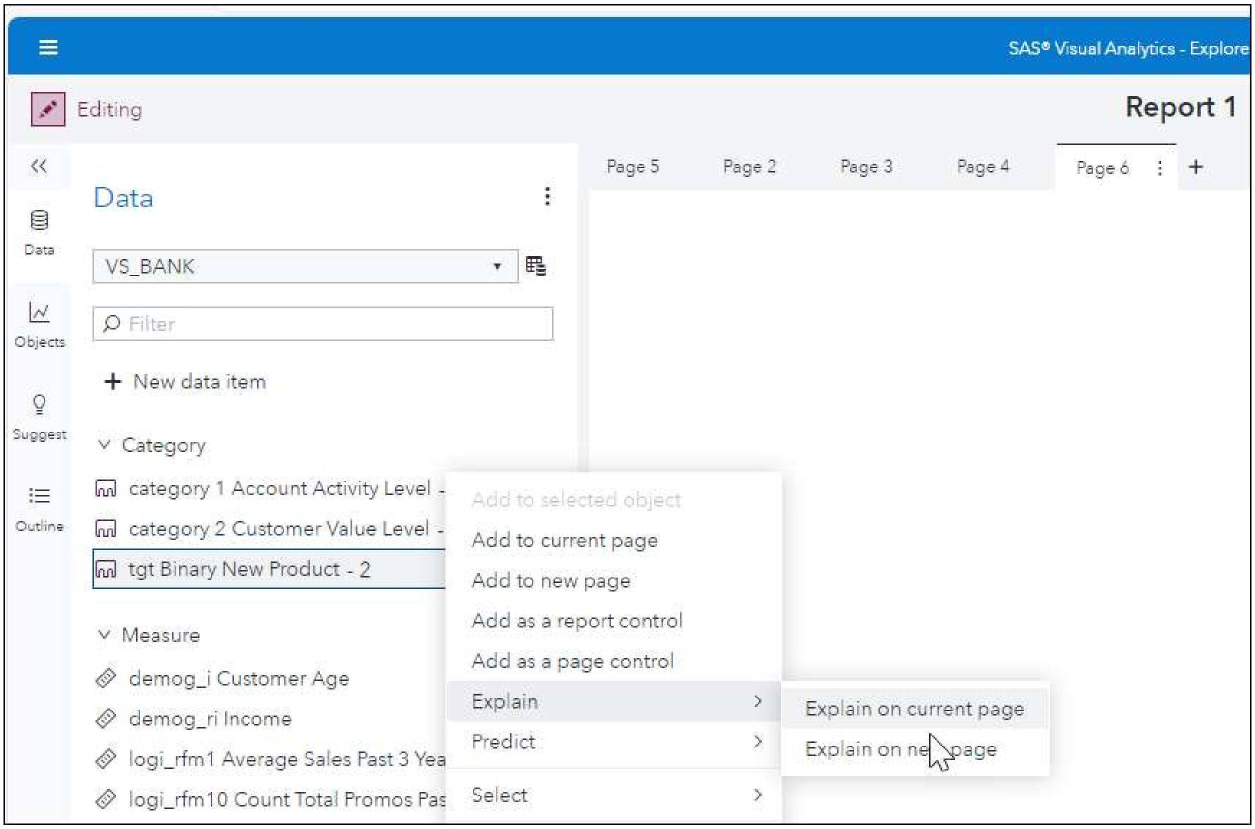
Displayed items (17):

- category 1 Account Activity Level - 3
- category 2 Customer Value Level - 5
- demog_i Customer Age
- demog_ri Income
- logi_rfm1 Average Sales Past 3 Years
- logi_rfm10 Count Total Promos Past Year
- logi_rfm11 Count Direct Promos Past Year
- logi_rfm12 Customer Tenure
- logi_rfm2 Average Sales Lifetime
- logi_rfm3 Avg Sales Past 3 Years Dir Promo Resp
- logi_rfm4 Last Product Purchase Amount
- logi_rfm5 Count Purchased Past 3 Years

15. You should have 17 Displayed items. Click **OK** to close the Show or Hide Data Items window.

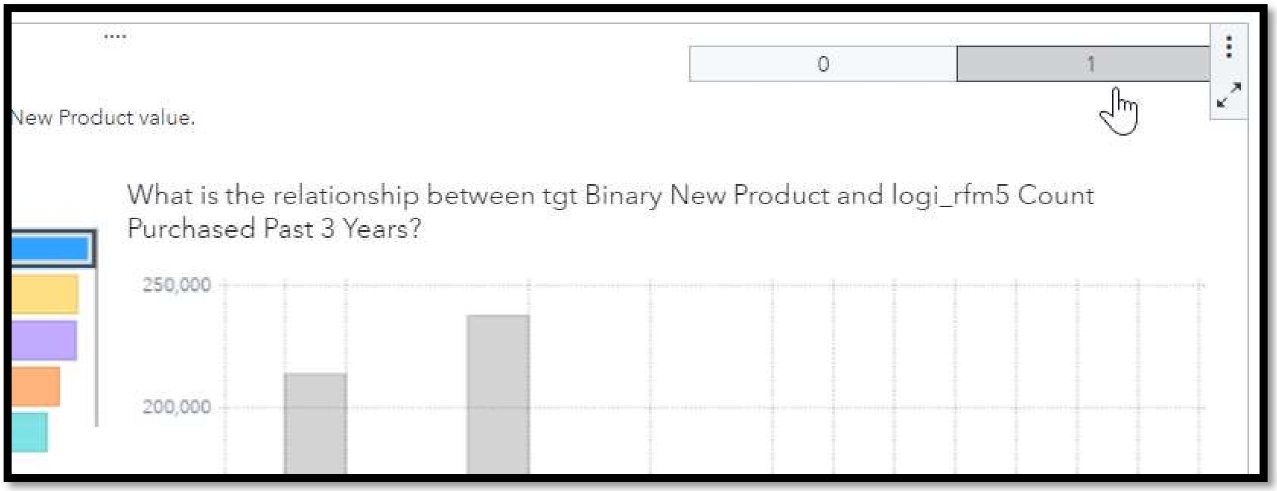
16. The data set contains more than one million rows and (is now filtered to) 16 explanatory columns plus one target variable. We will see more detail on the variables in our exploration, but they contain demographic information, account activity level, customer value level and various purchase behaviors.

A quick and easy way to begin exploring my data would be to create an automated explanation. The automated explanation reveals the most important underlying features for a target variable. In this example, I'm trying to understand whether an account will make a purchase (or not). Let's easily create that explanation in a report with one click. I right-click on the target variable **tgt Binary New Product** and select **Explain > Explain on current page**.

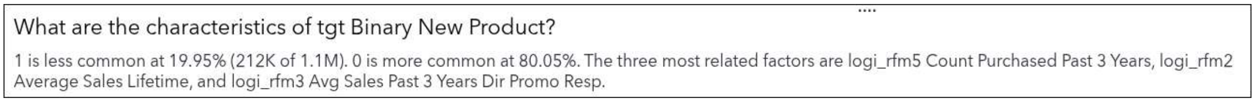


17. The resulting report reveals that my target variable has an 80% chance of being a 0. In other words, the majority of my customers were non-purchasers.

    Much of the report is aimed at explaining the most common value of 0 (non-purchasers), but honestly, we are more interested in the behavior of the purchasers (value of 1). Let's update the chart by selecting **1** in the button bar.


0
1
New Product value.
What is the relationship between tgt Binary New Product and logi_rfm5 Count Purchased Past 3 Years?
250,000
200,000

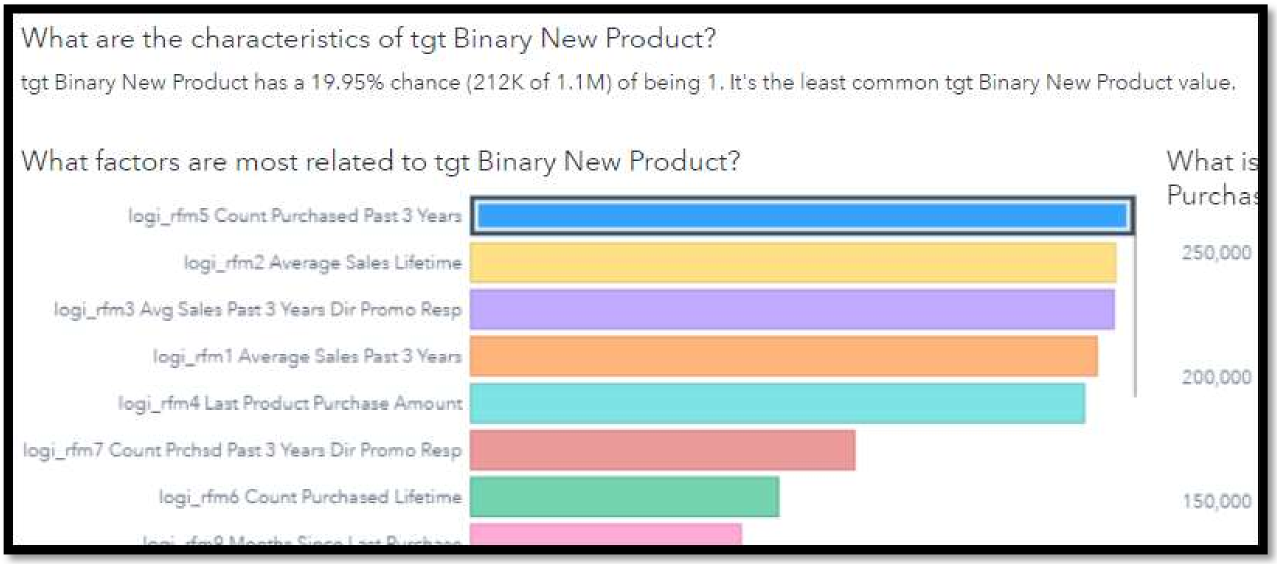
18. From the resulting report, I begin my data exploration and discover all kinds of interesting information about the target variable of customer purchase. You'll notice that the summary bar along the top has been updated to show that approximately 20% of the customers made a purchase (value of 1).



What are the characteristics of tgt Binary New Product?

1 is less common at 19.95% (212K of 1.1M). 0 is more common at 80.05%. The three most related factors are logi_rfm5 Count Purchased Past 3 Years, logi_rfm2 Average Sales Lifetime, and logi_rfm3 Avg Sales Past 3 Years Dir Promo Resp.

Then we can see under "What factors are most related to tgt Binary New Product?" that the following three variables are the most related factors: count purchased over the past 3 years, average sales over the lifetime, average sales over the past 3 years in response to a direct promotion. Of course, it makes sense that these three factors could have a large effect upon whether a customer would make a purchase or not. Notice that the top bar is already selected.

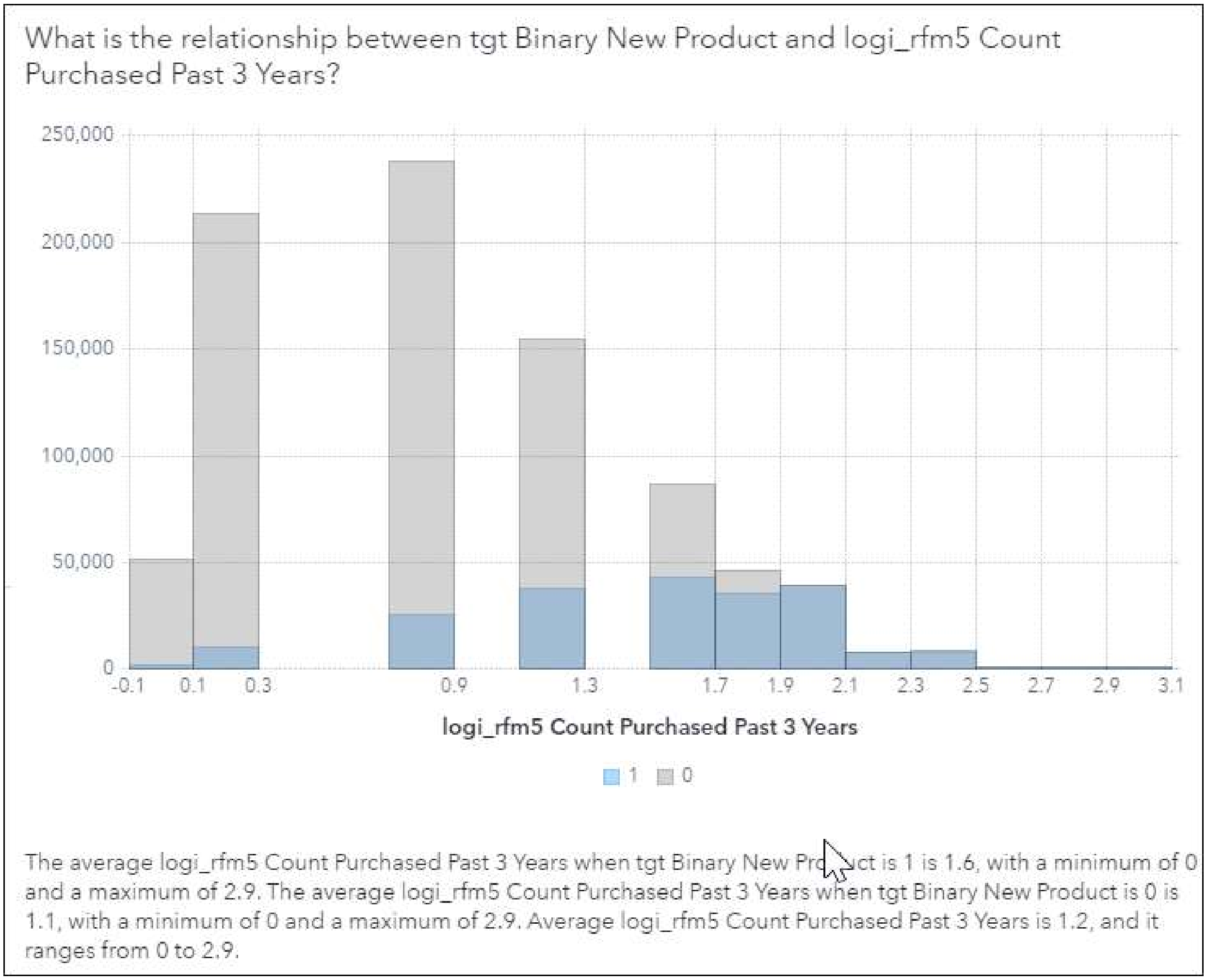


What are the characteristics of tgt Binary New Product?

tgt Binary New Product has a 19.95% chance (212K of 1.1M) of being 1. It's the least common tgt Binary New Product value.

What factors are most related to tgt Binary New Product?
logi_rfm5 Count Purchased Past 3 Years
logi_rfm2 Average Sales Lifetime
logi_rfm3 Avg Sales Past 3 Years Dir Promo Resp
logi_rfm1 Average Sales Past 3 Years
logi_rfm4 Last Product Purchase Amount
logi_rfm7 Count Prchsd Past 3 Years Dir Promo Resp
logi_rfm6 Count Purchased Lifetime
What is
Purchas
250,000
200,000
150,000

19. It would be interesting to understand the relationship between this top factor (count purchased over the past 3 years) and our binary target variable. Fortunately, we already have an automatically generated chart to help us. Let's examine "What is the relationship between tgt Binary New Product and logi_rfm5 Count Purchased Past 3 years?"

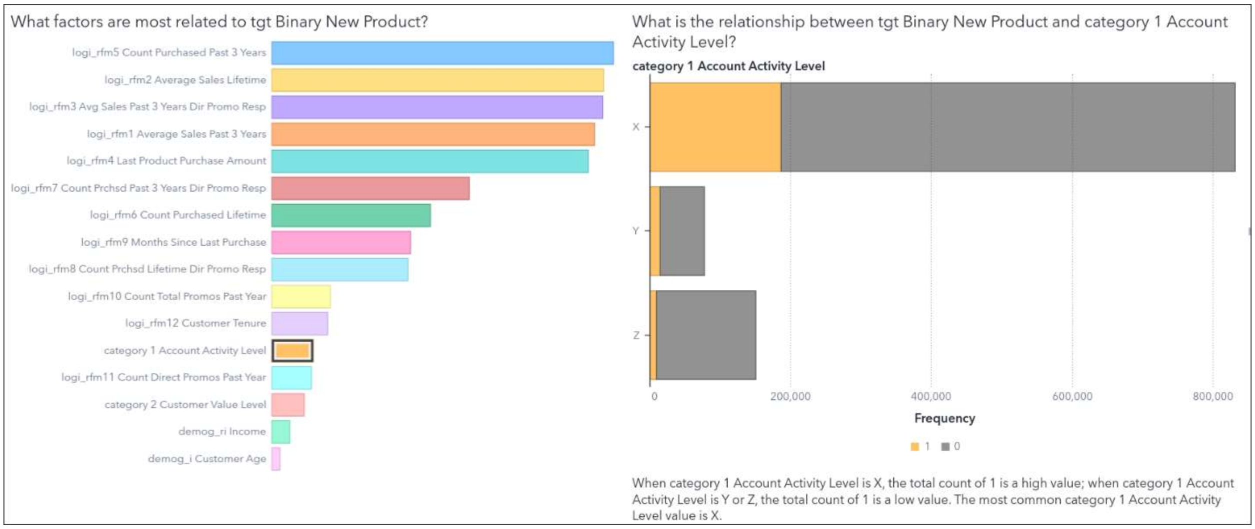


What is the relationship between tgt Binary New Product and logi_rfm5 Count Purchased Past 3 Years?

The average logi_rfm5 Count Purchased Past 3 Years when tgt Binary New Product is 1 is 1.6, with a minimum of 0 and a maximum of 2.9. The average logi_rfm5 Count Purchased Past 3 Years when tgt Binary New Product is 0 is 1.1, with a minimum of 0 and a maximum of 2.9. Average logi_rfm5 Count Purchased Past 3 Years is 1.2, and it ranges from 0 to 2.9.

We can see that for purchasers, the average number of products bought over the past 3 years is about 1.6. Keep in mind that our data was transformed, so in reality customers bought approximately 5 products on average.

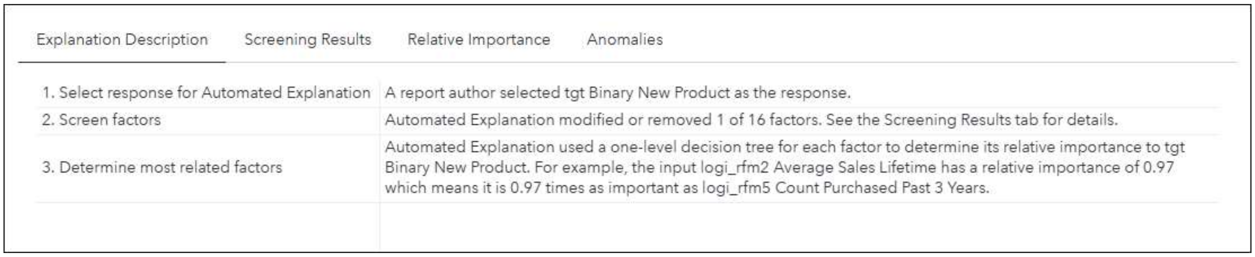
20. What happens to the automatic explanation if we are interested in a categorical input? To investigate the relationship between the account activity level and our target, select the **category 1 Account Activity Level** bar. The relationship chart automatically updates. It makes sense that the accounts with the highest activity (value of "x") has the majority of our purchasers.


What factors are most related to tgt Binary New Product?
logi_rfm5 Count Purchased Past 3 Years
logi_rfm2 Average Sales Lifetime
logi_rfm3 Avg Sales Past 3 Years Dir Promo Resp
logi_rfm1 Average Sales Past 3 Years
logi_rfm4 Last Product Purchase Amount
logi_rfm7 Count Prchsd Past 3 Years Dir Promo Resp
logi_rfm6 Count Purchased Lifetime
logi_rfm9 Months Since Last Purchase
logi_rfm8 Count Prchsd Lifetime Dir Promo Resp
logi_rfm10 Count Total Promos Past Year
logi_rfm12 Customer Tenure
category 1 Account Activity Level
logi_rfm11 Count Direct Promos Past Year
category 2 Customer Value Level
demog_ri Income
demog_i Customer Age
What is the relationship between tgt Binary New Product and category 1 Account Activity Level?
category 1 Account Activity Level
X
Y
Z
0
200,000
400,000
600,000
800,000
Frequency
1
0

When category 1 Account Activity Level is X, the total count of 1 is a high value; when category 1 Account Activity Level is Y or Z, the total count of 1 is a low value. The most common category 1 Account Activity Level value is X.

21. Before continuing with examining the rest of the automated explanation, let's reset the chart by re-selecting the top bar of the most related factors chart: **logi_rfm5 Count Purchased Past 3 Years**.

22. On the report, click (**Maximize**) to see the Details table.



1. Select response for Automated Explanation	A report author selected tgt Binary New Product as the response.
2. Screen factors	Automated Explanation modified or removed 1 of 16 factors. See the Screening Results tab for details.
3. Determine most related factors	Automated Explanation used a one-level decision tree for each factor to determine its relative importance to tgt Binary New Product. For example, the input logi_rfm2 Average Sales Lifetime has a relative importance of 0.97 which means it is 0.97 times as important as logi_rfm5 Count Purchased Past 3 Years.

The Explanation Description includes: the selected response for the automated explanation, the screen factors, and how the most related factors were determined. In this case, a one-level decision tree for each factor was used to determine the relative importance.

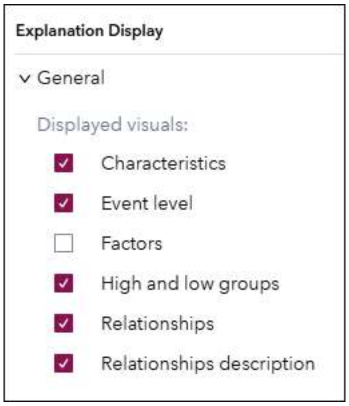
The Screening Results shows you steps that the Automated Explanation took to prepare your data for its analysis. It might remove some variables (for example, those that have a high number of missing values). It converts numeric columns with few distinct values to categories. It might even remove geographic variables like latitudes and longitudes from the analysis.

The Relative Importance shows you the values used in the most related factors chart.

Anomalies reveals any anomalies detected during the automated explanation.

23. In the upper right corner of the report, click (**Restore**) from the object toolbar to close the Details table and exit maximize mode.

24. Before we complete our investigation of the automated explanation, let's turn on an option to show us the most likely and least likely groups of purchasers. In the Options pane, turn on **High and low groups**. (Turn off **Factors** for more real estate.)



Explanation Display

v General

Displayed visuals:

☑ Characteristics

☑ Event level

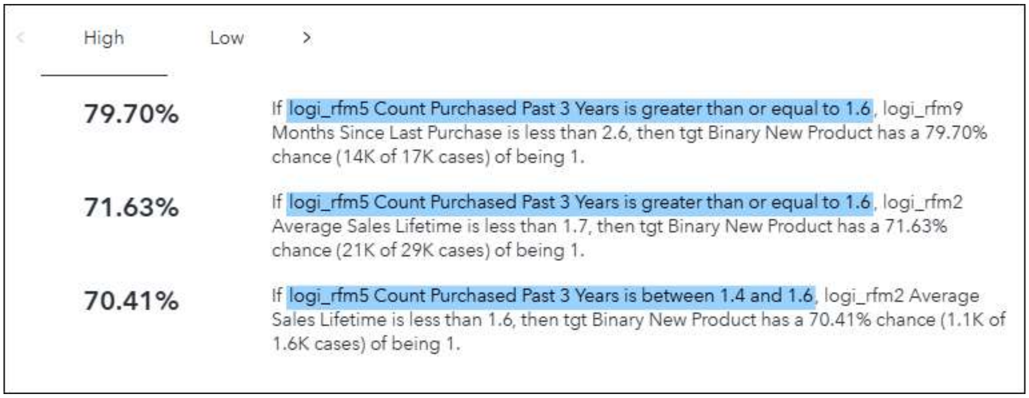
□ Factors

☑ High and low groups

☑ Relationships

☑ Relationships description

25. A new visual appears on the canvas of our automated explanation. On the High tab we are presented with the top three groups that are most likely to make a purchase. Let's examine the first group which has an almost 80% predicted probability of making a purchase. If the count purchased over the past 3 years is greater than or equal to a 1.6 **and** it has been less than 2.6 months since the last purchase, then a customer is very likely (79.70%) to make a purchase. In case you are curious, there are more decision trees being created in the background to give us all this wonderful information.

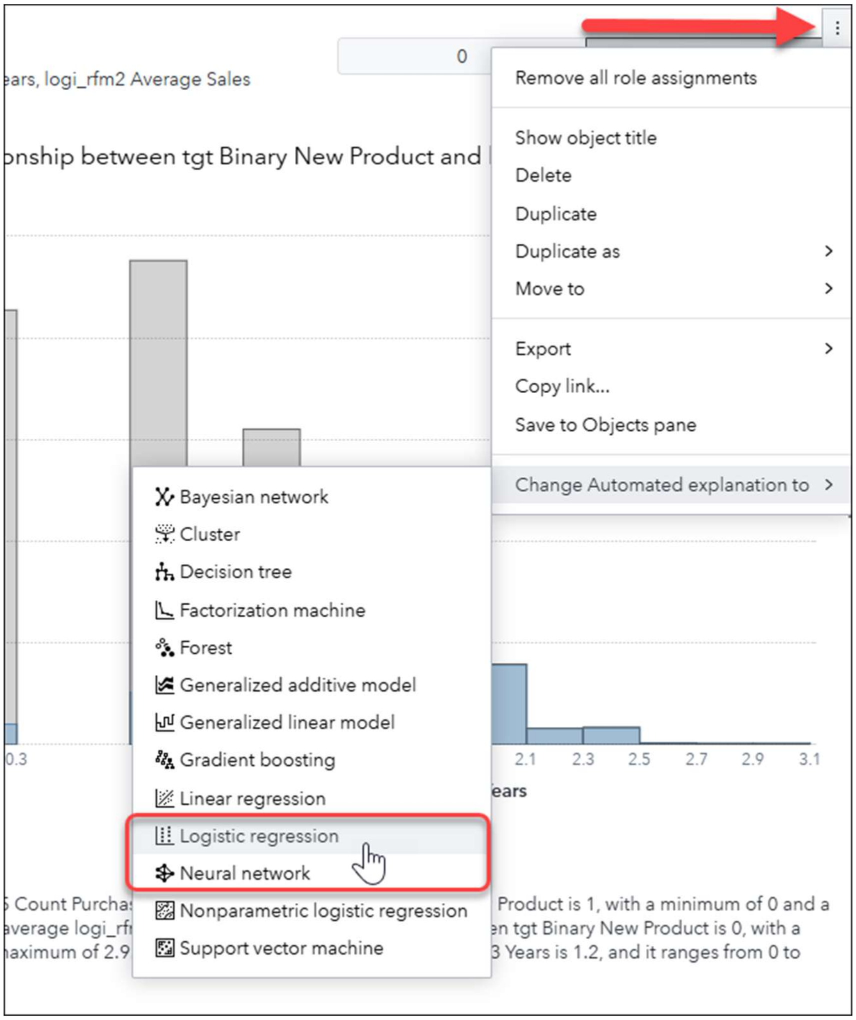


79.70% If logi_rfm5 Count Purchased Past 3 Years is greater than or equal to 1.6, logi_rfm9 Months Since Last Purchase is less than 2.6, then tgt Binary New Product has a 79.70% chance (14K of 17K cases) of being 1.

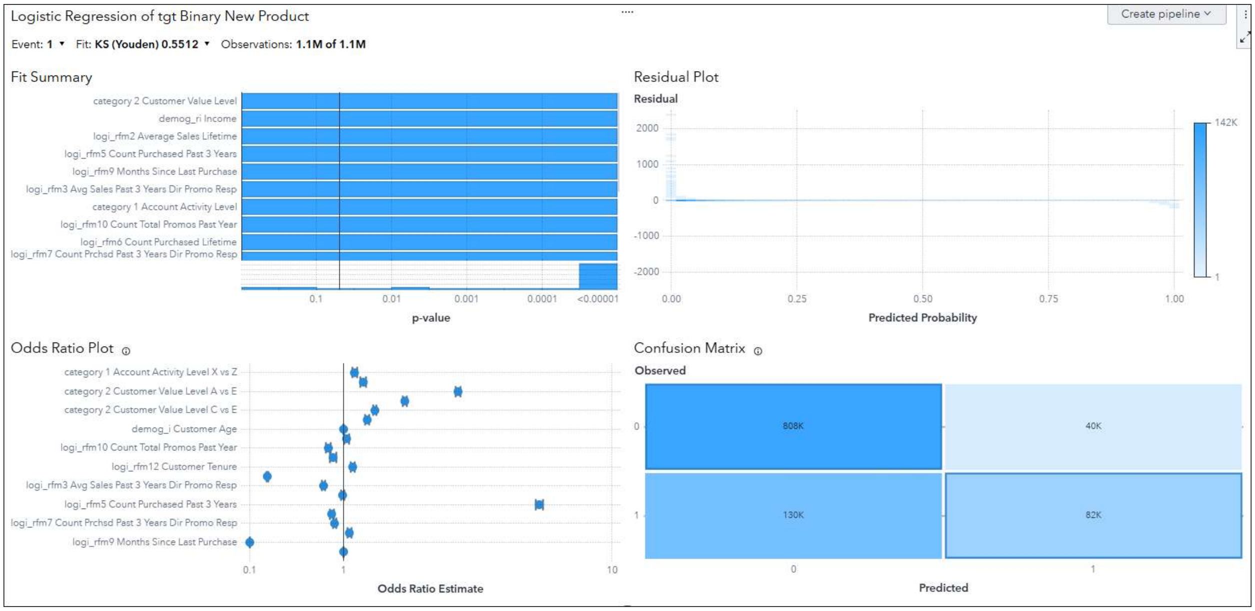
71.63% If logi_rfm5 Count Purchased Past 3 Years is greater than or equal to 1.6, logi_rfm2 Average Sales Lifetime is less than 1.7, then tgt Binary New Product has a 71.63% chance (21K of 29K cases) of being 1.

70.41% If logi_rfm5 Count Purchased Past 3 Years is between 1.4 and 1.6, logi_rfm2 Average Sales Lifetime is less than 1.6, then tgt Binary New Product has a 70.41% chance (1.1K of 1.6K cases) of being 1.

26. Now that we’ve done a bit of data exploration, let’s quickly and easily see how we can build a predictive model. I open the **Object menu** and select **Change Automated explanation to > Logistic Regression**.



27. I am still astounded at how easy it is to create models in SAS Viya. As you've seen, just a couple of clicks and I already built a predictive model! As a data scientist, being able to quickly explore data and efficiently build models are important skills. Let's take a quick look at the logistic regression results.



Logistic Regression of tgt Binary New Product

Event: 1 ▾ Fit: KS (Youden) 0.5512 ▾ Observations: 1.1M of 1.1M

Create pipeline
Fit Summary
category 2 Customer Value Level
demog_ri Income
logi_rfm2 Average Sales Lifetime
logi_rfm5 Count Purchased Past 3 Years
logi_rfm9 Months Since Last Purchase
logi_rfm3 Avg Sales Past 3 Years Dir Promo Resp
category 1 Account Activity Level
logi_rfm10 Count Total Promos Past Year
logi_rfm6 Count Purchased Lifetime
logi_rfm7 Count Prchsd Past 3 Years Dir Promo Resp
0.1
0.01
0.001
0.0001
<0.00001
p-value
Residual Plot
Residual
2000
1000
0
-1000
-2000
0.00
0.25
0.50
0.75
1.00
Predicted Probability
142K
1
Odds Ratio Plot
category 1 Account Activity Level X vs Z
category 2 Customer Value Level A vs E
category 2 Customer Value Level C vs E
demog_i Customer Age
logi_rfm10 Count Total Promos Past Year
logi_rfm12 Customer Tenure
logi_rfm3 Avg Sales Past 3 Years Dir Promo Resp
logi_rfm5 Count Purchased Past 3 Years
logi_rfm7 Count Prchsd Past 3 Years Dir Promo Resp
logi_rfm9 Months Since Last Purchase
0.1
1
10
Odds Ratio Estimate
Confusion Matrix
Observed
0
1
808K
40K
130K
82K
0
1
Predicted

From the Summary Bar at the top, we can see that the KS statistic is 0.5512. We could use that model fit statistic to compare it to another model and determine which model had the higher value. The Fit Summary pane reveals that 14 of the 16 effects are significant at a .05 significance level. The two predictors at the bottom of the chart are not significant at .05. There is a large odds ratio of 6 for *Count purchased over the last three years*. This means that for each additional product a customer purchases, the customer is 6-times more likely to be a purchaser. The Residual Plot shows that there do not appear to be any outliers in the residual data. And finally, the Confusion Matrix reveals that our model correctly identified 81,853 of the purchasers and 808,181 of the non-purchasers.

End of Demonstration