SAS® Visual Analytics 7.2, 7.3, and 7.4: Getting Started with Analytical Models

SAS® Documentation

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SAS® Visual Analytics 7.2, 7.3, and 7.4: Getting Started with Analytical Models

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August 2017

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Contents

Using This Book

Audience

This book covers the basics of building and comparing models in SAS Visual Analytics Explorer using the model-building capabilities provided by SAS Visual Statistics. The examples in this book show you how to create an input or segmentation variable, build models for measure and classification targets, and compare completed models. The emphasis is on building and comparing models so that you are familiar with the visualizations provided by SAS Visual Statistics.

Requirements

Prerequisites

If you choose to perform the tasks in this book, you need the following software, information, and privileges:

- a link to a working deployment of SAS Visual Statistics 7.2, 7.3, or 7.4
- a supported web browser (see the SAS support site for supported versions)
- a supported version of the Adobe Flash Player (see the SAS support site for supported versions)
- an account that can log on to the working deployment
- the input data provided for this book

- model building capabilities (without the necessary capabilities, you cannot access the visualizations provided by SAS Visual Statistics)

System Requirements

Detailed system requirements, including support for additional web browsers, are available on the SAS support site.

1

Introduction

About SAS Visual Statistics

SAS Visual Statistics is an add-on modeling tool to SAS Visual Analytics. The modeling capabilities of SAS Visual Statistics are provided in SAS Visual Analytics Explorer (the explorer). The visualizations provided by SAS Visual Statistics include a linear regression, a logistic regression, a generalized linear model (GLM), and a clustering tool. In addition, you gain access to a more powerful decision tree visualization, which includes the ability to interactively train a decision tree by manually selecting which branches to prune, split, or train. Model assessment statistics are available in the core decision tree visualization. To export your models, you can export model score code for any model or export derived columns that contain prediction information (predicted values, residuals, cluster ID, and so on).

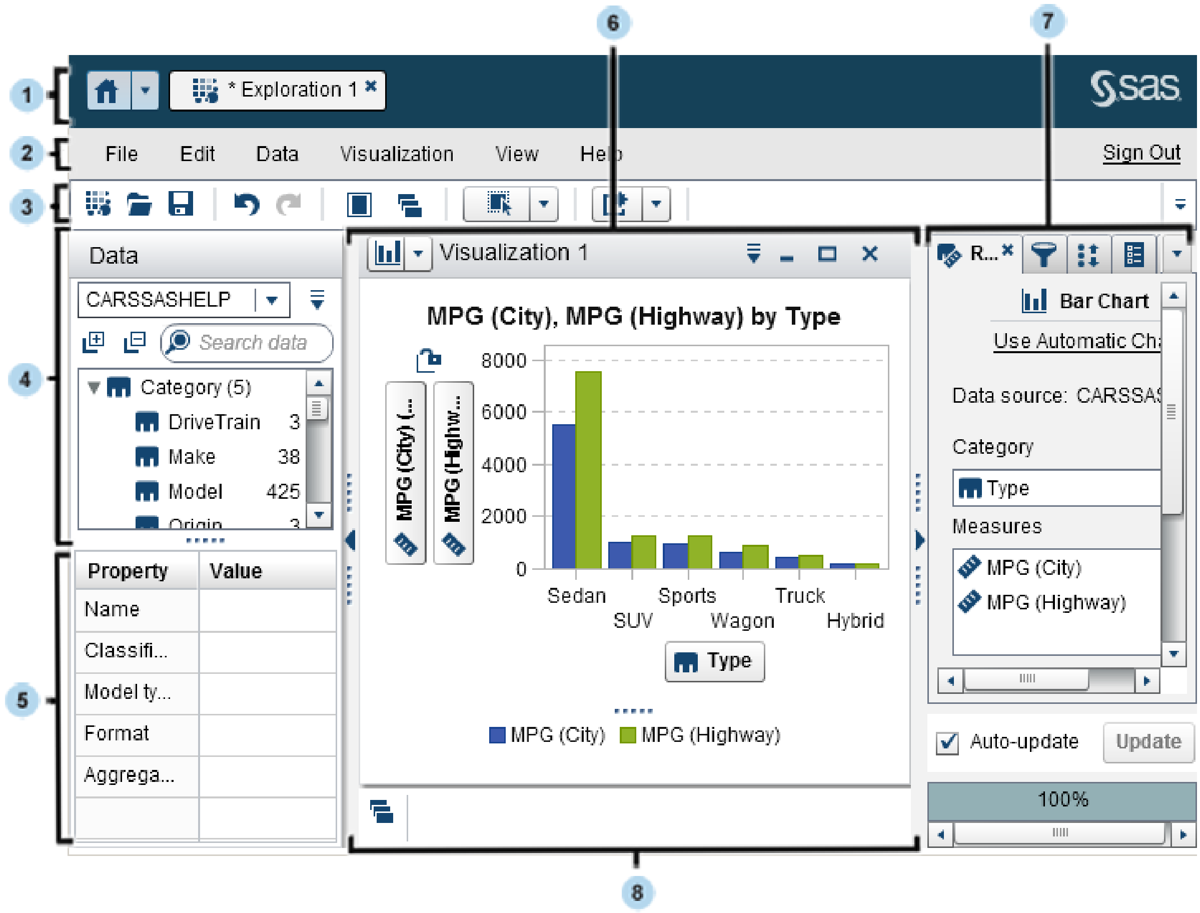
Within SAS Visual Statistics, you can perform a variety of tasks critical to creating good predictive models. These tasks include data segmentation (supervised and unsupervised), supervised variable transformation, stratified modeling, outlier detection, interactive feature creation, data filtering, and post-model visualization. The examples in this book are intended to familiarize you with the SAS Visual Statistics interface and workflow. Therefore, not all of these tasks are covered in this book.

2

Your First Look at the SAS Visual Analytics Interface

The Explorer User Interface

The Explorer



1 The application bar enables you to return to the home page and to access other parts of SAS Visual Analytics and other SAS applications that integrate with the home page. You can access your recently created or viewed reports, explorations, stored processes, data queries, or other objects in your recent history. Buttons are displayed for each open application.

2 The menu bar offers common tasks, such as creating a new exploration.

3 The toolbar enables you to manage your explorations and visualizations.

4 The **Data** pane enables you to manage the data that is used in your visualizations.

5 The data properties table enables you to set data item properties.

6 The workspace displays one or more visualizations.

7 The right pane's tabs enable you to set properties and data roles, create filters and ranks, set global parameter values, and use comments.

8 The dock contains any minimized visualizations.

Menus and Toolbars

From the SAS Visual Statistics main menu, you are able to access all of the features of the application.

The SAS Visual Statistics toolbar enables you to quickly access frequently used tasks:

Icon	Description
▦	Creates a new exploration.
▣	Maximizes the modeling workspace.
▥	Returns the modeling workspace to the default view.
⟋	Creates a linear regression model.
⋮	Creates a logistic regression model.
⟋	Creates a generalized linear model (GLM).
⊥	Creates a decision tree model.
▽	Creates a cluster model.

Icon	Description
	Compares two or more models.

The Data Pane

The **Data** pane enables you to access all of the variables in your data set. Variables are sorted into **Category** and **Measure** variable groups. By default, character variables are considered category variables and numeric variables are considered measure variables. Numeric variables with a finite number of levels can be converted into category variables.

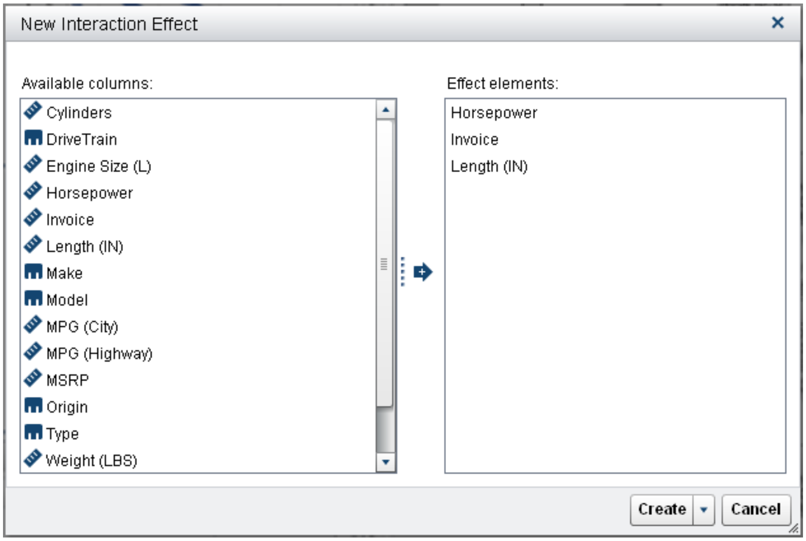
You can create variable interactions and calculated items in the **Data** pane.

When you enter something into the **Search data** field, only those variables that contain the search term are displayed. Search terms are not case sensitive.

To collapse the variable groups, click ⊟ to the left of the **Search data** field. To expand the variable groups, click ⊞ to the left of the **Search data** field.

The **Data** pane drop-down list icon, ▾, is located in the upper right corner of the **Data** pane. The following items are of interest, but not a complete list of options:

- **New Interaction Effect** enables you to create interaction effects to use in your visualizations.



Available columns:

- Cylinders
- DriveTrain
- Engine Size (L)
- Horsepower
- Invoice
- Length (IN)
- Make
- Model
- MPG (City)
- MPG (Highway)
- MSRP
- Origin
- Type
- Weight (LBS)

Effect elements:

- Horsepower
- Invoice
- Length (IN)

In the New Interaction Effect window, you move variables from the **Available columns** area to the **Effect elements** area. You can drag and drop a variable, double-click a variable, or use the arrows in the center of the window. After you have moved variables to the **Effect elements** area, click **Create** to create a single interaction. Alternatively, click ▾ to specify whether you want to **Create one interaction** or **Create two-way interactions**.

When you choose **Create two-way interactions**, all of the possible pairs of interactions for the selected variables are created, except for square terms. To create a square term, move two copies of a variable into the **Effect elements** area, and click **Create**.

- **Data Properties** displays the name, classification, data type, model type, and format for each variable in the data set.
- **Measure Details** opens the Measure Details window. The Measure Details window provides summary statistics and a histogram for each of the measure variables.
- **Show/Hides Items** enables you to specify what variables are displayed in the **Data** pane. Variables in the **Visible items** area are displayed in the **Data** pane. Variables in the **Hidden items** area are not displayed.

  To move variables from one area to the other, drag and drop the variable, double-click a variable, or use the arrows in the center of the window. You can move multiple variables by selecting them first, and then either dragging and dropping them or using the arrows.

Click **OK** to close the Show or Hide Items window and save your changes.

- **Sort Items** enables you to specify whether you want to sort the variables in ascending or descending order.

The Right Pane

The right pane contains the **Roles**, **Properties**, and **Filters** tabs. Together, these three tabs define the modeling parameters. The **Roles** tab specifies what variables are used in the model and their purposes in the model. The **Properties** tab enables you to specify features that are unique to each model. The **Filters** tab enables you to subset the data that is modeled.

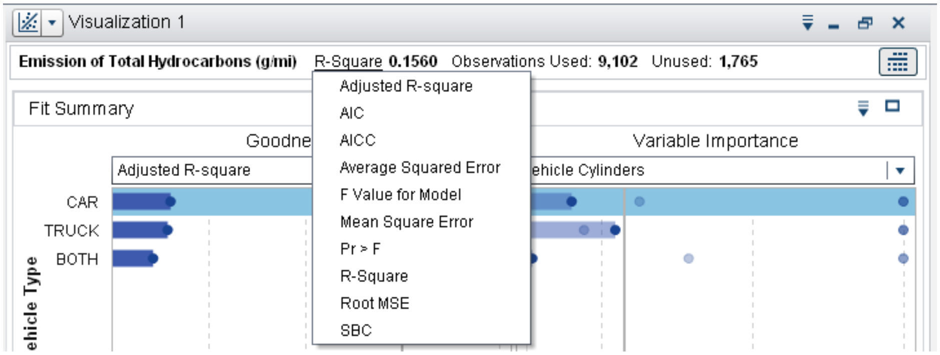
Tab	Description
Roles	Enables you to add variables to your model. From the **Data** pane, drag and drop a variable that you want to use to a role on the **Roles** tab. Alternatively, you can select several variables and drag and drop them onto the model pane. In this case, each variable is assigned to the first valid and available role. If there is no response variable, then the first valid variable is assigned to the **Response** role. This method never assigns **Group By**, **Frequency**, **Filter**, or **Weight** variables. You can use the ▼ icon to add or remove variables from each individual field.
Filters	Enables you to specify variables that are used to filter the data set. You can filter on category variables, measure variables, or both. To add a filter variable, drag and drop that variable from the **Data** pane to the **Filters** tab or use the ▼ icon. To remove a filter variable, click ✕ next to that variable's name.
Ranks	Enables you to specify rank variables. Rank variables subset the data in your visualization to display either the top or the bottom aggregated value for a category. To add a rank variable, drag and drop that variable from the **Data** pane onto the **Ranks** tab.

Tab	Description
Properties	Enables you to specify features of the model. The available options vary based on the selected model.
Comments	Enables you to enter comments about the current model.
Parameters	Enables you to view any parameters that affect a calculated item that is used by the current model.

The Model Pane

The model pane contains the modeling results and plots. Because the windows available depend on the selected model, this section focuses on the common elements for all models. Specific information for each model is available in the *SAS Visual Analytics: User's Guide*.

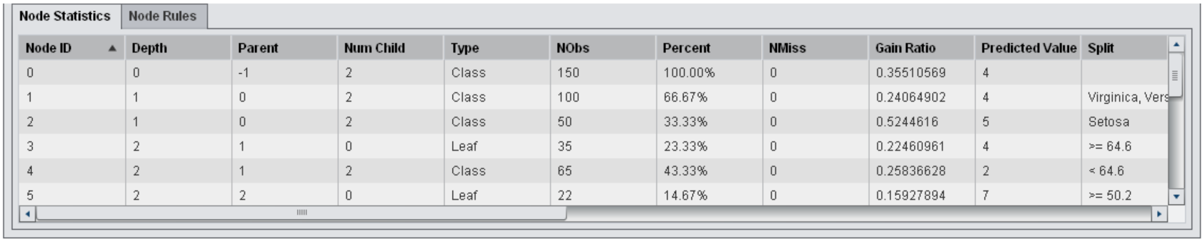
The summary bar displays the response variable, model evaluation criterion (when available), and the number of used and unused observations in the model. To see all of the available model evaluation criteria, click the name of the current model evaluation criterion in the summary bar to open a pop-up menu.



Emission of Total Hydrocarbons (g/mi) R-Square 0.1560 Observations Used: 9,102 Unused: 1,765

On the right side of the summary bar, there is the ▦ icon. Click ▦ to open the details table at the bottom of the model pane.

An example details table from a decision tree model is shown below. The specific information in each details table varies based on the model.



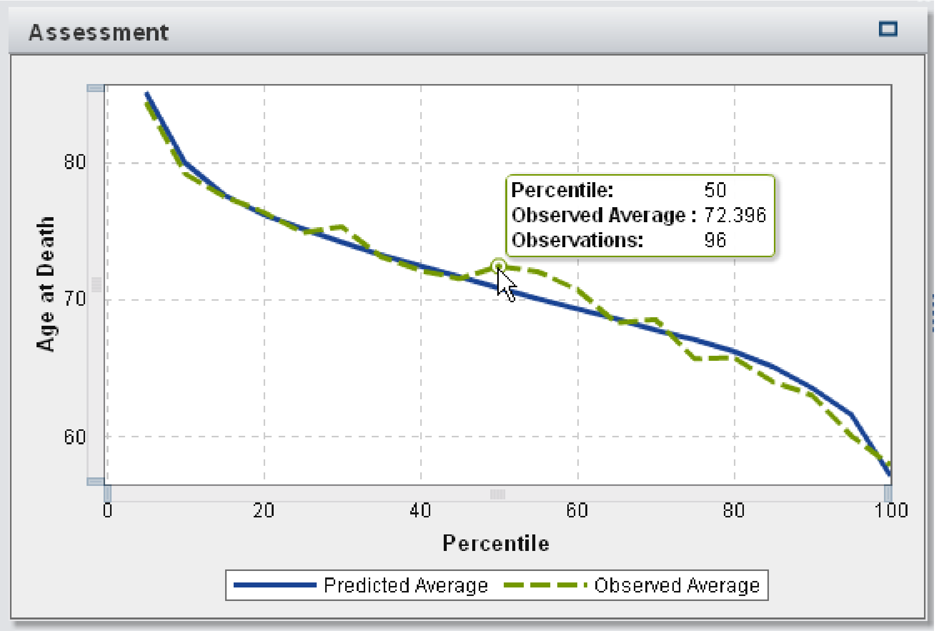
Node ID	Depth	Parent	Num Child	Type	NObs	Percent	NMiss	Gain Ratio	Predicted Value	Split
0	0	-1	2	Class	150	100.00%	0	0.35510569	4	
1	1	0	2	Class	100	66.67%	0	0.24064902	4	Virginica, Vers
2	1	0	2	Class	50	33.33%	0	0.5244616	5	Setosa
3	2	1	0	Leaf	35	23.33%	0	0.22460961	4	>= 64.6
4	2	1	2	Class	65	43.33%	0	0.25836628	2	< 64.6
5	2	2	0	Leaf	22	14.67%	0	0.15927894	7	>= 50.2

To maximize a window, click □. This hides all of the other windows in the model pane, but does not hide the details table. To restore the default view, click ❐.

The Gallery on page 31 contains a sample screenshot and description for each window.

Window Name	Available In
Fit Summary	Linear, Logistic, GLM
Residual Plot	Linear, Logistic, GLM
Assessment	Linear, Logistic, GLM, Decision Tree
Influence Plot	Linear and Logistic
Tree	Decision Tree
Leaf Statistics	Decision Tree
Cluster Matrix	Cluster
Parallel Coordinates	Cluster

In every window, if you position your mouse pointer over an object, a tooltip provides specific information about that object. The information varies based on the plot that is displayed. For example, in the following image, the tooltip shows the percentile (in the bin), observed average value in that bin, and the number of observations in that bin.



Percentile: 50
Observed Average : 72.396
Observations: 96

Whenever a range of values is shown or selected, the interval is half-open. The minimum value is included in the interval. The maximum value is excluded from the interval. This affects heat maps, the parallel coordinates plot, and any other displayed or selected interval.

Managing Explorations and Models

Explorations

A SAS Visual Statistics exploration consists of one or more models and the associated data. You can create an exploration using any of the following methods:

- Select **File** ▸ **New Exploration** from the main menu. Select a data source, and then click **Open**.
- Click in the toolbar.

Models

To create a model, click the icon for that model type in the toolbar.

To rename a model, select **Edit** ▶ **Rename** from the main menu. Enter a new name in the **New name** field, and click **OK**. This affects the current model in the model pane.

To duplicate a model, click the ▾ icon in the upper right corner of the model, and select **Duplicate**. This creates a model named Copy of *Model Name* with the same settings as the copied model. You might duplicate a model if you have a good model, but you want to try out some enhancements without overwriting the current model. This feature enables you to leave the original model intact while you adjust the duplicate model. This affects the current model in the model pane.

To delete a model, click the × in the upper right corner of the model. Every time you delete a model, you are asked to confirm the action.

3

Data Discovery

About the Tasks in This Chapter

Data discovery is the process of investigating your data, its characteristics, and its relationships before analysis. This includes a variety of techniques that ensure that your data creates statistically valid models. In this chapter, you will learn how to identify a stratification variable and create a new input variable using the cluster visualization. However, before you can get started, you must download an input data set and import it into SAS Visual Analytics.

Import the Data

This example uses the 2014 Emission and Fuel Economy Test Data published by the United States Environmental Protection Agency. You can use the information in this data set to create four different predictive models.

The data is available as a SAS data set on the SAS Visual Analytics product documentation page. Complete the following steps to import this data into the explorer:

1. In a web browser, go to http://support.sas.com/documentation/onlinedoc/va/index.html. Save the **SAS Visual Analytics: Getting Started with Analytical Models EPA_CARS** data set on your local machine. Note where you saved this data set.

2. Sign in to SAS Visual Analytics, and open the explorer. Click **Select a Data Source** in the window that appears.

3. In the **Import Data** area of the Open Data Source window, click **SAS Data Set**.

4. In the window, navigate to where you saved the EPA_CARS data set. Select it, and click **Open**.

5. In the Import SAS Data Set window, accept all of the default options.

6. Click **OK**.

Identify a Segmentation Variable

When working with a large data set, it often contains several heterogeneous subgroups. Therefore, it is beneficial to segment the data into these subgroups and create a separate model for each subgroup. Sometimes, a category variable exists in your data set that is suitable for segmentation. If a pre-defined segmentation variable does not exist, you can derive segmentation information from a decision tree or cluster. This example shows both cases.

In the **Data** pane, find the category variable **Vehicle Type**. Notice that this variable contains three distinct values. If you visualize this variable, you can see that most vehicles are classified as cars, some are classified as trucks, and a smaller portion are classified as both a car and a truck. You use the **Vehicle Type** variable as a segmentation variable for the linear regression model and GLM that you create in the next section.

Create a Segmentation Variable from a Cluster

You can segment data by clustering the data. A cluster is a group of observations that are similar in some way that is suggested by the data. SAS Visual Statistics includes a cluster visualization that automatically segments the data based on the properties and variables that you specify. After clustering the data, you can derive a cluster ID variable that specifies which cluster each observation belongs to. This cluster ID variable is then used in your models. For the following example, you want to cluster the data on several other measures.

1 Click to create a new visualization.

2 Click to specify that this visualization is a cluster.

3 Drag and drop the variables **Vehicle Cylinders**, **Vehicle EngineSize (l)**, and **Vehicle Horsepower** onto the visualization. By default, five clusters are created.

4 Click ▾ in the visualization title bar, and select **Derive a Cluster ID Variable**. Enter `Vehicle Clusters` in the **Name** field. Click **OK**.

   This new cluster ID variable contains the cluster assignment for each observation in the data. Observations with missing values are assigned to their own cluster. You will use this variable in the models that you create in the next sections.

   Note: Even though five clusters are created, this variable contains six measurement levels (distinct values). This is because there is an additional measurement level created for observations with missing values.

5 Save the exploration.

You can also use the decision tree visualization to segment the data. After creating a decision tree, you can derive a leaf ID variable that contains the leaf assignment information for each observation.

The cluster ID variable and the leaf ID variable can be used in subsequent visualizations as either an effect or a group by variable. The cluster ID and leaf ID variables persist even if you delete the visualization that created them.

4

Modeling a Measure Variable

About the Tasks in This Chapter

Linear regression models and GLMs are two predictive models used for measure target variables. In this chapter, you create both a linear regression and a GLM to predict the amount of total hydrocarbon emissions for each vehicle. Then, you compare these two models using multiple fit statistics.

Create a Linear Regression

A linear regression attempts to predict the value of a measure response variable as a linear function of one or more effects. The linear regression model uses the least squares method to determine the model.

To create the linear regression for this example, complete the following steps:

1. Click to create a new visualization.

2. Click to specify that this visualization is a linear regression.

3. Drag and drop the variable **Emission of Total Hydrocarbons (g/mi)** into the **Response** field on the **Roles** tab.

4. Drag and drop the variables **Vehicle Clusters**, **Vehicle Manufacturer**, **Test Procedure**, **Vehicle Cylinders**, **Vehicle MPG**, **Vehicle Gears**, and **Vehicle Weight (lbs)** onto the visualization. SAS Visual Analytics automatically creates a linear regression model using these variables as the effects.

5. Drag and drop the variable **Vehicle Type** into the **Group By** field on the **Roles** tab. This specifies that **Vehicle Type** is the segmentation variable.

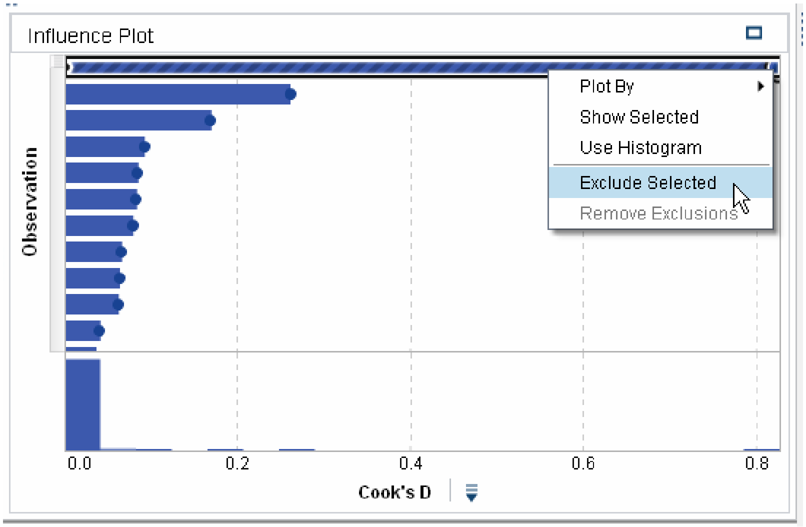
   The results windows are updated. Instead of creating one model for the entire input data set, separate models are created for each measurement level of the group by variable. In this example, that means that separate models were created based on a vehicle's classification as a car, a truck, or both.

6. Select the **Properties** tab in the right pane. Select **Informative missingness**. Enabling this property indicates that missing values are used in the model.

7. In the Fit Summary window, click the **CAR** segment.

   In the Influence Plot, Cook's D is the default influence statistic. Notice that the first bar in this plot is significantly larger than all the other bars. From this, you can guess that the observations represented by this bar are outliers, and you should exclude them from the model.

   To exclude these observations, click the bar to select it. Right-click the bar, and select **Exclude Selected**.



The model for the **CAR** segment is updated to account for the excluded observations.

8 Save the exploration.

Create a Generalized Linear Model

A generalized linear model (GLM) is an extension of a traditional linear model that allows the population mean to depend on a linear predictor through a nonlinear link function. A GLM requires that you specify a distribution and a link function. The distribution should match the distribution of the response variable. The link function is used to relate the response variable to the effect variables.

To create the GLM for this example, complete the following steps:

1 In the **Data** pane, select the variable **Emission of Total Hydrocarbons (g/mi)**. Click ▾, and select **Measure Details**.

2 In the Measure Details window, notice that the distribution of emissions of total hydrocarbons (g/mi) is not normal. The shape of the distribution suggests that an exponential distribution might be appropriate for the GLM.

Close the Measure Details window.

3. Click to create a new visualization.

4. Click to specify that this visualization is a GLM. Maximize the visualization.

5. Drag and drop the variable **Emission of Total Hydrocarbons (g/mi)** into the **Response** field on the **Roles** tab.

6. Select the **Properties** tab in the right pane. Select **Informative missingness**.

7. For the **Distribution** property, select **Exponential**.

8. Drag and drop the variables **Vehicle Clusters**, **Vehicle Manufacturer**, **Vehicle Axle Ratio**, **Vehicle Cylinders**, **Vehicle Gears**, **Vehicle MPG**, and **Vehicle Weight (lbs)** onto the visualization. SAS Visual Analytics automatically creates a GLM using these variables as the effects.

9. Drag and drop the variable **Vehicle Type** into the **Group By** field on the **Roles** tab. This specifies that **Vehicle Type** is used as a segmentation variable.

   The results windows are updated. As with the linear regression, separate models are created based on a vehicle's classification as a car, a truck, or both.

10. Save the exploration.

Compare Your Models

You can compare the performance of these two models using the model comparison visualization. In the explorer, model comparison requires that the response variable, level, and group by variable are identical in the compared models. The effects used in each model can differ.

To compare the models in this example, complete the following steps:

1. Click to create a new model comparison.

2. In the Model Comparison window, **Response** should already contain the variable **Emission of Total Hydrocarbons (g/mi)**. Select the variable **Vehicle Type** for **Group By**. If you used a group by variable in only one of the models that you created, you cannot compare these two models.

3. Click » between the **Available models** area and the **Selected models** area to add both visualizations to the model comparison.

4. Click **OK**.

5. Review the results windows for the model comparison. The default segment chosen is **CAR**. This is displayed in the summary bar at the top of the visualization.

   Because **Emission of Total Hydrocarbons (g/mi)** is an interval target, the model comparison visualization displays an Assessment plot. This plot compares either the observed average value or predicted average value between each model at each percentile. Notice that these models are relatively similar in regard to both the observed or predicted average.

   In the Fit Statistic window, the default displayed value is the average square error (ASE). Hold your mouse pointer over the bar for each visualization to see that the ASE value for the linear regression is better.

   The fit statistic **Observed Average** displays the observed average value at the specified percentile. After selecting **Observed Average**, you can change the displayed percentile with the slider on the **Properties** tab.

   This information is also in the details table. In addition to ASE, you can view the sum of squared errors (SSE). Notice that the SSE for these two models favors the linear regression.

6. In the summary bar, click the word **CAR**, and select **TRUCK** to compare the results for the truck segment. Explore the Assessment and Fit Statistic windows to notice the differences and similarities between the two models.

7. Repeat your exploration for the **BOTH** segment.

8. Save the exploration.

Note: Model comparisons do not persist between sessions. If you sign out of SAS Visual Analytics and want to return to this model comparison, then you must re-create it.

5

Modeling a Category Variable

About the Tasks in This Chapter

In this chapter, you create both a decision tree and a logistic regression model to predict vehicle type based on a variety of effects. The decision tree is built by hand with interactive training tools provided by SAS Visual Statistics. You compare the decision tree and logistic regression model using multiple fit statistics.

Create a Decision Tree

A decision tree creates a hierarchical segmentation of the input data based on a series of rules applied to each observation. Each rule assigns an observation to a segment based on the value of one effect. Rules are applied sequentially, which results in a hierarchy of segments within segments.

To create the decision tree for this example, complete the following steps:

1 Click to create a new visualization.

2 Click to specify that this visualization is a decision tree.

3 Drag and drop the variable **Vehicle Type** into the **Response** field on the **Roles** tab.

At this point, there is only a single node in your decision tree. The predicted value for this node is **CAR** because it is the most frequent measurement level in that node.

4 On the **Roles** tab, click **Advanced**. Select **TRUCK** as your event level. Click **OK**.

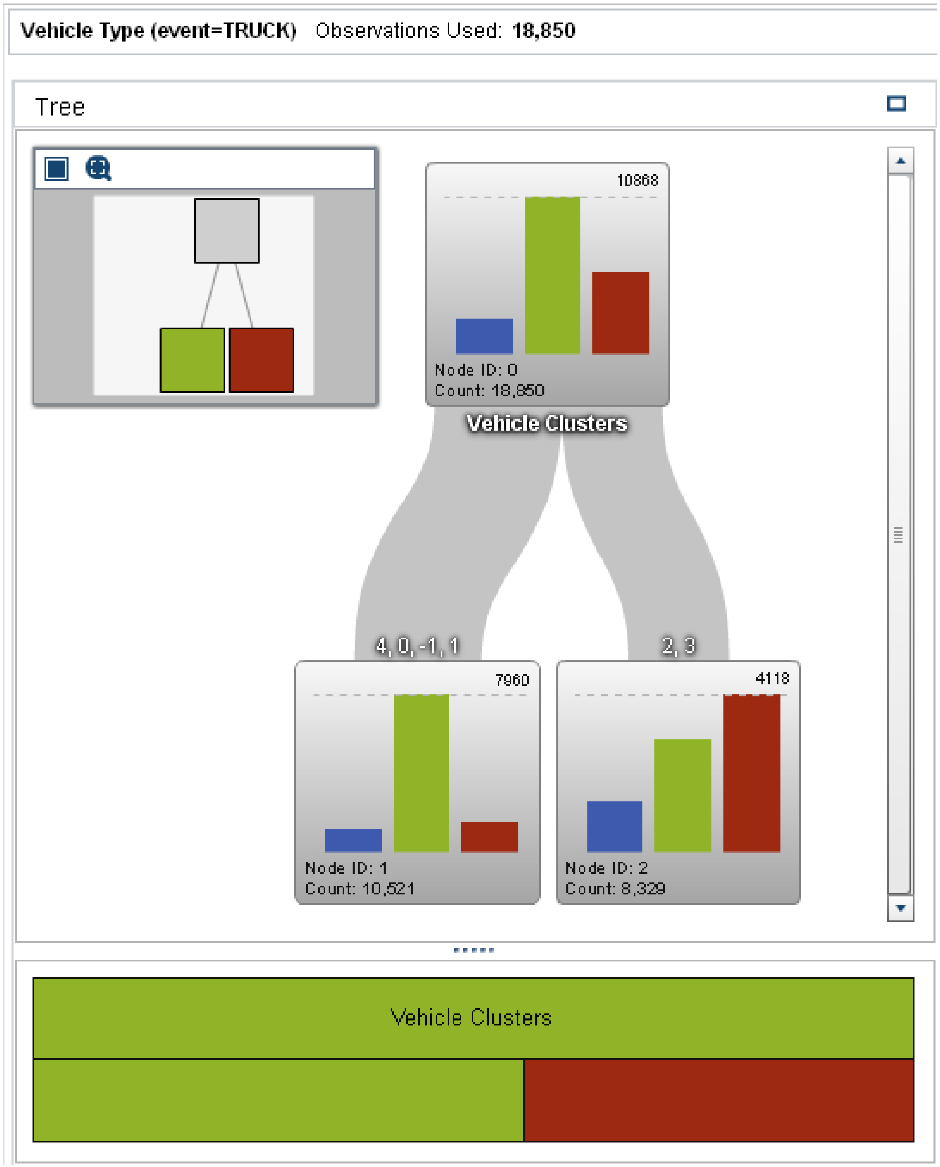
This selection indicates that you want to predict whether an observation is a truck for model comparison purposes. The two other measurement levels are grouped together as not trucks.

5 Select the **Properties** tab in the right pane. For **Maximum levels**, specify `2`.

Select **Show diagnostic plots**. In the Assessment window, select the **Misclassification** plot. Observe this plot as you make changes to the decision tree to see how well your model classifies the data.

Enabling this property ensures that the smallest possible decision tree is created when you add predictors to the tree. In the following steps, you add a variety of predictors to the tree and interactively train the tree.

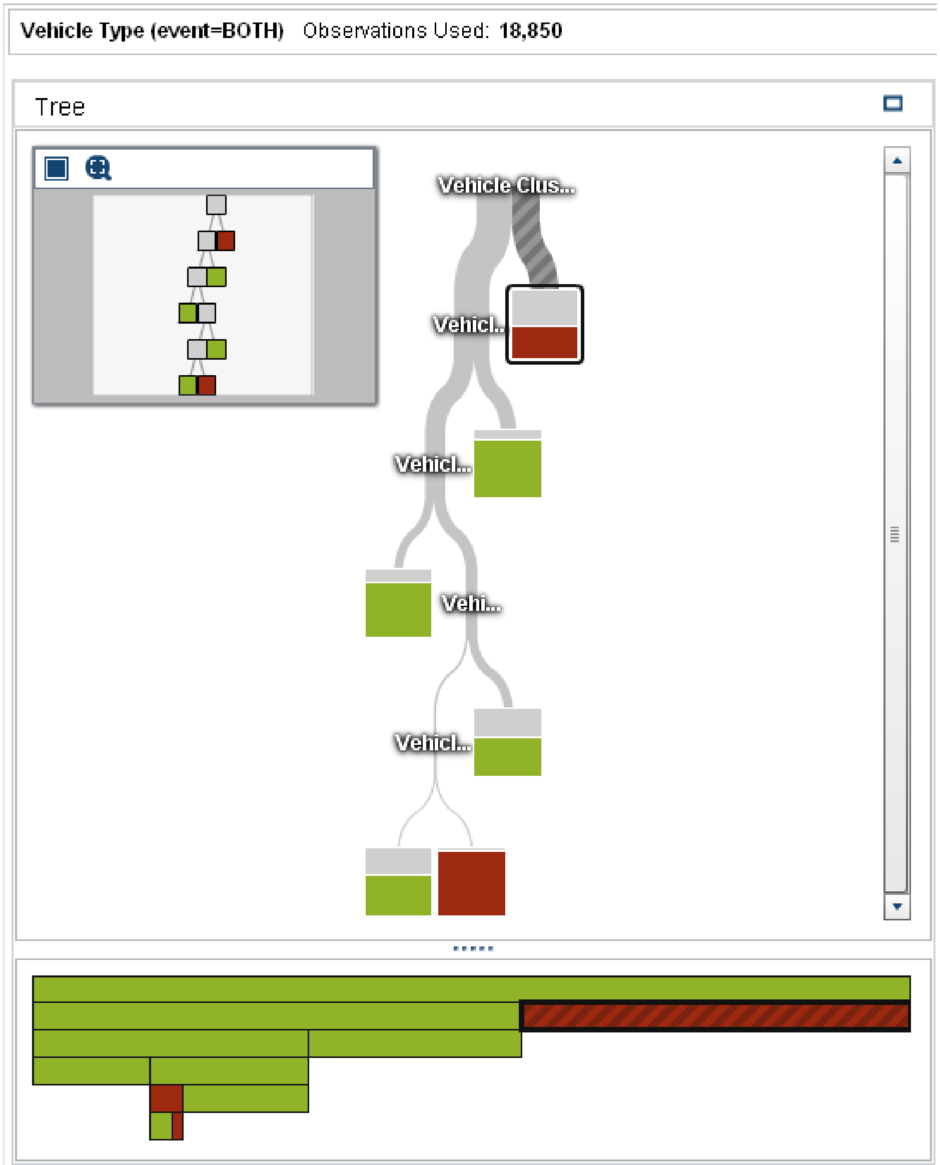
6 Drag and drop the variables **Vehicle Clusters**, **Vehicle Axle Ratio**, **Vehicle Cylinders**, **Vehicle EngineSize (l)**, **Vehicle Gears**, **Vehicle Horsepower**, and **Vehicle MPG** onto the visualization. A two-level decision tree is created.



Vehicle Type (event=TRUCK) Observations Used: **18,850**

7 Select the leaf node that contains vehicle clusters **4**, **0**, **-1**, and **1**. Right-click on this node, and select **Train**. The Train Decision Tree window appears.

The variable **Vehicle EnglineSize (l)** is automatically selected for training because it has the greatest log worth of all the variables. **Maximum depth of subtree** is set to 6, which indicates that up to six additional levels can be added to the current decision tree. Click **OK**.

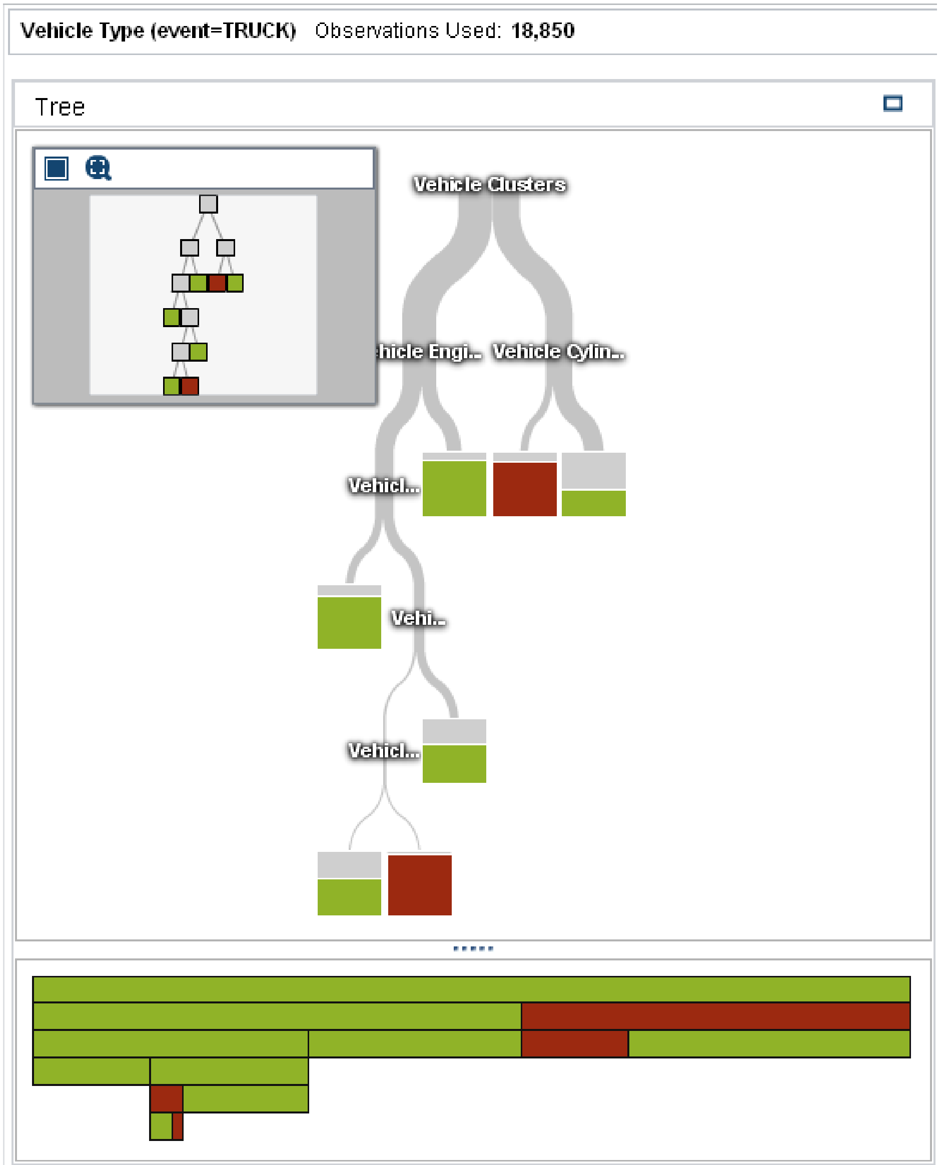


Vehicle Type (event=BOTH) Observations Used: 18,850

8 Select the node that contains only vehicle clusters **2** and **3**. Right-click on this node, and select **Train**. The Train Decision Tree window appears.

The variables **Vehicle EngineSize (I)**, **Vehicle Clusters**, and **Vehicle Cylinders** all have an equal log worth. Select **Vehicle Cylinders**, and click **OK**.

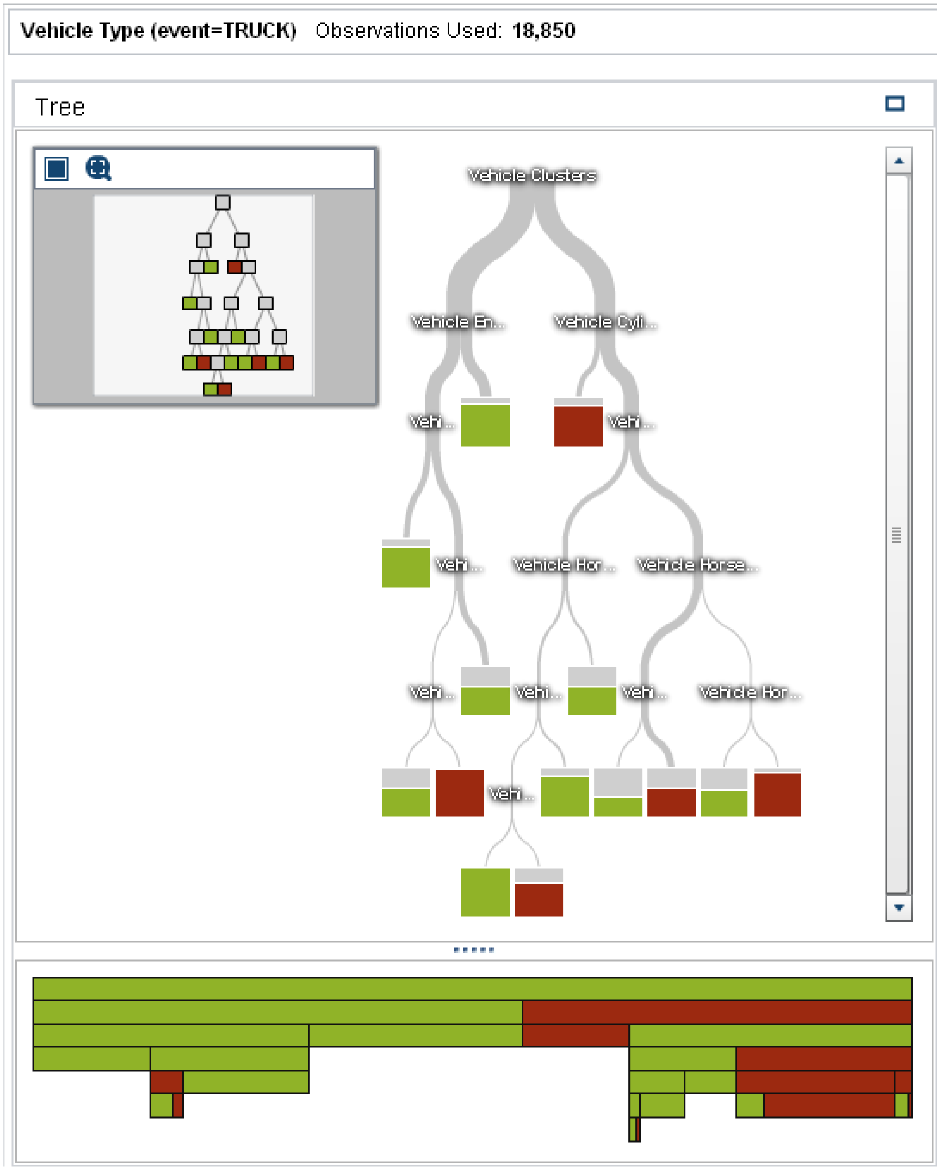
Only one additional level is added to the decision tree. Check the **Misclassification** plot in the Assessment window to confirm that the number of misclassifications decreased.



Vehicle Type (event=TRUCK) Observations Used: 18,850

9 Repeat the training for node 12, which is the node that contains vehicle clusters **2** and **3** and in which vehicle cylinders is less than 6.1. Right-click on this node, and select **Train**. **Vehicle Horsepower** has the greatest log worth, so select it, and click **OK**.

Zoom out to view the full tree. Your final decision tree should resemble the following image:



Vehicle Type (event=TRUCK) Observations Used: **18,850**

Tree

10 Save the exploration.

Create a Logistic Regression

A logistic regression attempts to predict the value of a binary response variable. A logistic regression analysis models the natural logarithm of the odds ratio as a linear combination of the explanatory variables.

To create the logistic regression for this example, complete the following steps:

1. Click to create a new visualization.
2. Click to specify that this visualization is a logistic regression. Maximize the visualization.
3. Drag and drop the variable **Vehicle Type** into the **Response** field on the **Roles** tab.
4. On the **Roles** tab, beside the **Response** field, click **Advanced**. Select **TRUCK** as your event level. Click **OK**.
5. Drag and drop the variables **Vehicle Clusters**, **Emission of Total Hydrocarbons (g/mi)**, **Vehicle Axle Ratio**, **Vehicle Cylinders**, **Vehicle EngineSize (l)**, **Vehicle Gears**, **Vehicle Horsepower**, **Vehicle MPG**, and **Vehicle Weight (lbs)** onto the visualization. SAS Visual Analytics automatically creates a logistic regression model using these variables as the effects.
6. Select the **Properties** tab in the right pane. Select **Informative missingness**.
7. Save the exploration.

Compare Your Models

You can compare the performance of these two models using the model comparison visualization. In the explorer, model comparison requires that the response variable, level, and group by variable are identical in the compared models. The effects used in each model can differ.

To compare the models in this example, complete the following steps:

1 Click to create a new model comparison.

2 In the Model Comparison window, select **Vehicle Type** in the **Response** field. Select **TRUCK** in the **Level** field.

3 The logistic regression and decision tree should be available for comparison. Click » between the **Available models** area and the **Selected models** area to add both visualizations to the model comparison.

4 Click **OK**.

5 The default model comparison statistic is the **Misclassification rate**. In this example, the logistic regression outperforms the decision tree. That is, it misclassifies significantly fewer observations than the decision tree. Use the details table to compare all of the available fit statistics. From these statistics, it is obvious that the logistic regression outperforms the decision tree.

6 Save the exploration.

Note: Model comparisons do not persist between sessions. If you sign out of SAS Visual Analytics and want to return to this model comparison, then you must re-create it.

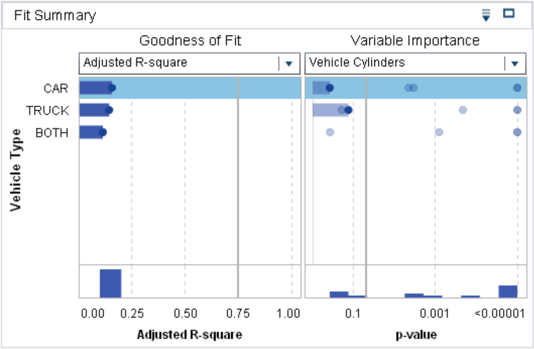
6

Quick Reference

Gallery

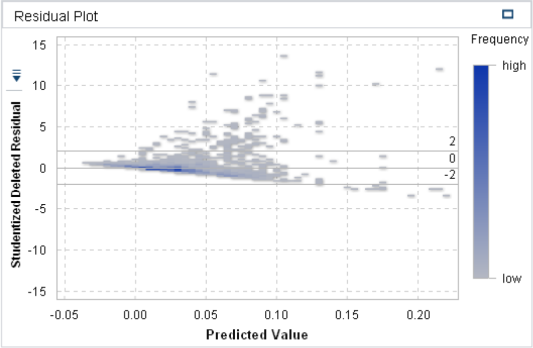
This is an illustrated gallery of plots and graphs found in SAS Visual Statistics.

TIP Use the following images for orientation. Actual appearance and functionality are affected by the underlying data, any styles that you apply, and the interface that you are using.

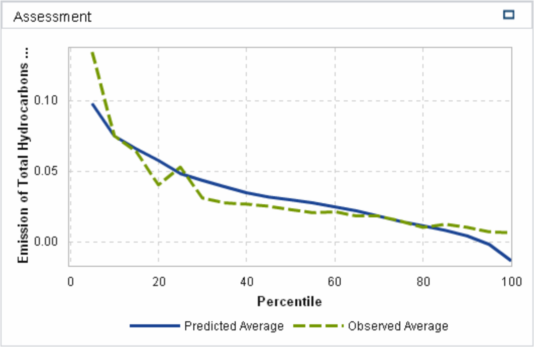


Displays the *p*-value of each modeling variable on a log scale. The alpha value, plotted as -log(alpha), is shown as a vertical line that you can click and drag to adjust. A histogram of the *p*-values is displayed at the bottom of the window.

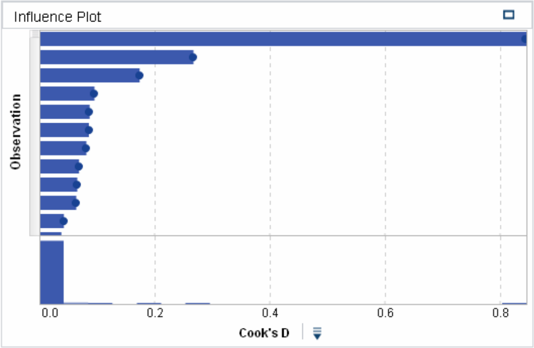
This window is divided when a group by variable is used. The left side lists the groups and the right side condenses the *p*-values for each group into a single linear scatter plot. You can click on a group on the left side to change the Residual, Influence, and Assessment plots to show only the results for that group.



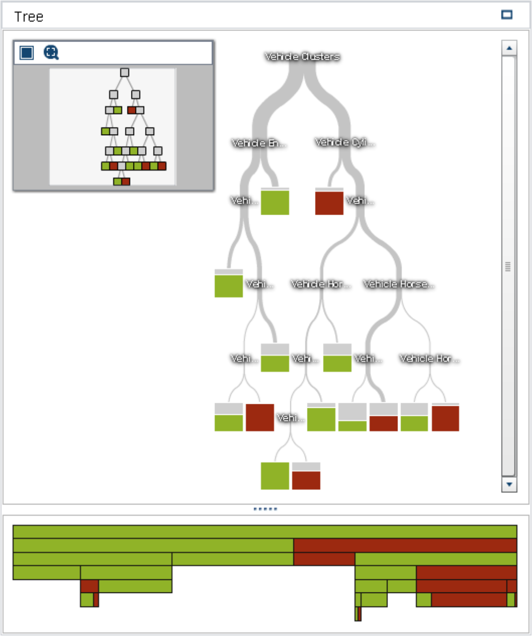
Displays various residual plots for the model. When the plot labels are buttons, you can select the values that are plotted on that axis. Each model has a unique set of plot combinations available.



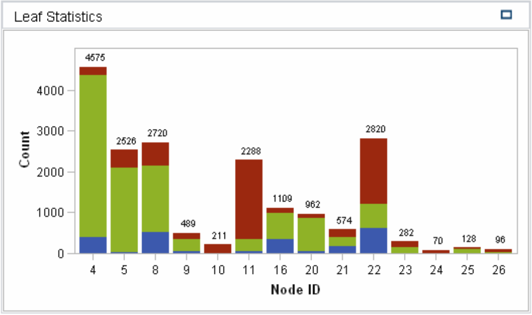
For measure target variables, Assessment plots the average predicted and observed values against the binned data set. For category target variables, it provides the Lift, ROC, and Misclassification plots.



Plots each observation against various computed statistics. The X axis label is a button that enables you to determine what is plotted. Each model has a unique set of plot combinations available.

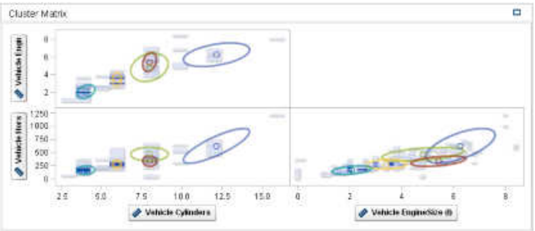


Displays the decision tree and the decision treemap. You can interactively train the decision tree from this window. Use the scroll wheel on your mouse to zoom in or out on the location of the mouse pointer.

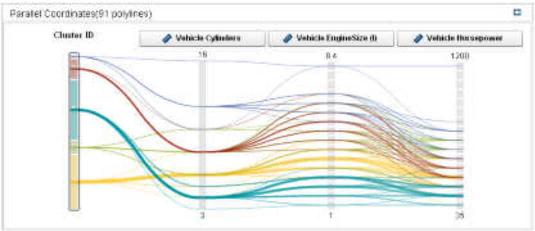


Leaf Statistics

Provides a stacked histogram of the response variable for each leaf node in the decision tree.



Displays the two-dimensional projection of every cluster for each pair of modeling variables. To view a larger plot of an individual projection, right-click in that cell, and select **Open**.



Displays a color-coded strand for each observation, initially sorted by cluster membership. You can restrict the display to observations that match specific clusters or ranges of the modeling variables.

Where to Find Additional Documentation

The most current technical resources for SAS Visual Analytics are available on the SAS Visual Analytics page on the SAS support site.

Your experience with SAS software should be as smooth as possible. Please submit your feedback.

Recommended Reading

- SAS Visual Analytics User’s Guide
- SAS Visual Analytics: Getting Started with Exploration and Reporting

For a complete list of SAS publications, go to sas.com/store/books. If you have questions about which titles you need, please contact a SAS Representative:

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