Wrocław University of Technology

Internet Engineering

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APPLICATION PROGRAMMING: DATA MINING AND DATA WAREHOUSING

PRACTICAL GUIDE

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Contents

Introduction

The purpose of this “Guide to Data Mining and Data Warehousing” is to present the practical perspective of these technologies. This guide is intended to be used by the participants of the “Application Programming: Data Mining and Data Warehousing” course as the accompanying material prepared to supplement the theoretical part with application examples. Familiarity with the concepts and theory presented in the course materials is assumed and required to efficiently follow examples developed in this guide, although experience or familiarity with data mining and data warehousing software is not necessary.

Application examples shown here are based on samples from real life datasets, are formulated based on real life problems, and are implemented using practical tools: SAS Enterprise Miner software for the data mining part, and MS SQL Server Integration Services and Analysis Services for the data warehousing part. The most efficient way to proceed with this guide is to actively follow these examples, and to learn-by-doing, hence the guide will familiarize users with many features of the software tools used. As such it can be useful for self-paced or guided lab practice in data mining and data warehousing technologies. For this purpose, the sample datasets elaborated in this guide will be made available to participants of the course.

The data mining part of this guide is focused on predictive modelling. We show how subsequent steps of *data mining process*, as guided by standard data mining methodologies, are practically implemented in Enterprise Miner. We introduce tools for data sampling, illustrate various techniques for explanatory analysis of data and discuss methods of data transformation to be used prior to building predictive models. Finally, we apply various classification models and demonstrate in-depth analysis of predictive performance of these models. Special consideration is given to the challenging problem of classification based on highly imbalanced data. We discuss several approaches to improve recognition of the rare class (i.e., the class under-represented in data), and show how these can be implemented in Enterprise Miner. We also illustrate some methods to fine-tune performance of classifiers.

The data warehousing part presents a sample project in which a multidimensional data analysis / OLAP system is designed and implemented. We demonstrate sample tools for implementation of ETL (Extract-Transform-Load) scripts, we design the logical multidimensional model of data, and we finally design and implement a multidimensional cube.

PART I Data Mining

The purpose of this practical guide to data mining is to learn how data mining methods / tools can be used to solve predictive modelling tasks, in particular for building classification models based on real life data.

This guide introduces readers to the data mining tool SAS Enterprise Miner (ver. 6.x), which is an advanced system to support data mining tasks in commercial, massive data environments. Enterprise Miner provides a comprehensive set of tools to realize subsequent stages of the data mining *process,* following the SEMMA methodology (acronym derived from the steps of data mining process: Sample, Explore, Modify, Model, Assess). These steps consist in:

- Sample step: involves sampling very large data sets, including simple random or more advanced statistical sampling techniques used to create representative or oversampled smaller data sets from very large databases. As part of the Sample step, Enterprise Miner also provides tools for data preparation (merging, filtering, etc., or for sophisticated transformation using SAS 4GL language).
- Explore step: involves initial exploration of data in order to understand inconsistencies in data and to later design required data cleaning / transformation steps. Enterprise Miner provides tools for statistical analyses, interactive graphical exploration or clustering of data.
- Modify step: involves data modification / preparation prior to model building. Enterprise Miner provides tools for missing value imputation, transformation of variables, variable selection and dimensionality reduction (such as Principal Component Analysis).
- Model step: involves building statistical or machine learning models for classification and regression, such as decision trees, neural networks, regression methods and nearest neighbours. Boosting techniques, meta models and user created models are also possible.
- Assessment step: involves analysis of predictive performance of the models and comparison of competing models using various measures and techniques (e.g., with ROC curves or using cut-off analysis). Assessment also involves management of the scoring programmes (in Enterprise Miner the scoring programmes can be exported in the form of SAS 4GL, C language, Java or PMML codes).

In addition to predictive modelling, Enterprise Miner also provides a number of tools used in other branches of data mining such as clustering, association rules mining, time series analysis, web mining (web log analysis).

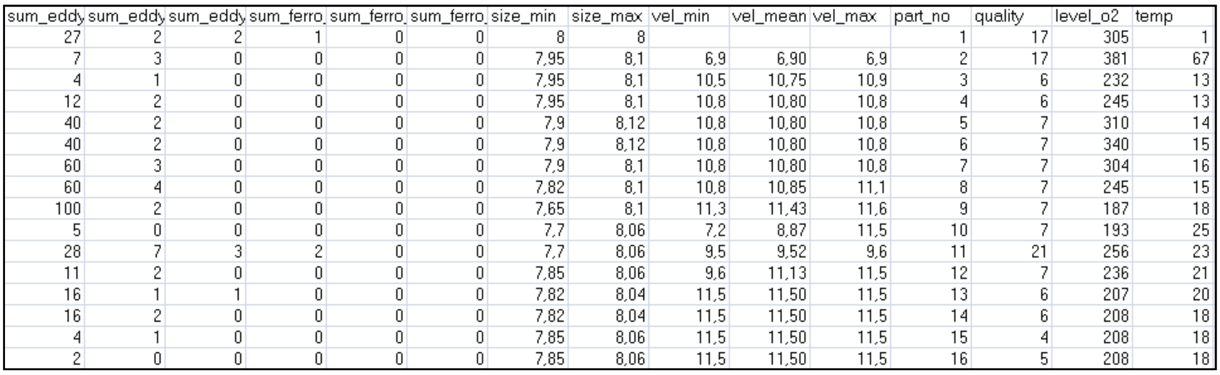
In this guide, we focus on predictive modelling; we demonstrate a classification task realized on a real life dataset.

Formulation of the Problem Solved in this Guide

The sample data mining task solved in this guide consists in building a classifier for assessment of quality of products manufactured by a company. Quality assessment will be attempted based on parameters of the production process recorded by a number of sensors along the production line. The classifier will be built using historical database, where known quality of products is given alongside with process monitoring data. The task involves:

- Building a mathematical model of relationship between the product quality and production process parameters,
- Estimation of predictive performance, i.e., expected error rate when the classifier is used for new data, i.e., to assess quality of a new production batch.

The process monitoring data analyzed in this guide comes from a copper wire production plant, where the items produced are rolls of copper wire. A sample of the source data is shown in Figure 1 and variable names are listed in Table 1.



sum_eddy	sum_eddy	sum_eddy	sum_ferro_	sum_ferro_	sum_ferro_	size_min	size_max	vel_min	vel_mean	vel_max	part_no	quality	level_o2	temp
27	2	2	1	0	0	8	8				1	17	305	1
7	3	0	0	0	0	7,95	8,1	6,9	6,90	6,9	2	17	381	67
4	1	0	0	0	0	7,95	8,1	10,5	10,75	10,9	3	6	232	13
12	2	0	0	0	0	7,95	8,1	10,8	10,80	10,8	4	6	245	13
40	2	0	0	0	0	7,9	8,12	10,8	10,80	10,8	5	7	310	14
40	2	0	0	0	0	7,9	8,12	10,8	10,80	10,8	6	7	340	15
60	3	0	0	0	0	7,9	8,1	10,8	10,80	10,8	7	7	304	16
60	4	0	0	0	0	7,82	8,1	10,8	10,85	11,1	8	7	245	15
100	2	0	0	0	0	7,65	8,1	11,3	11,43	11,6	9	7	187	18
5	0	0	0	0	0	7,7	8,06	7,2	8,87	11,5	10	7	193	25
28	7	3	2	0	0	7,7	8,06	9,5	9,52	9,6	11	21	256	23
11	2	0	0	0	0	7,85	8,06	9,6	11,13	11,5	12	7	236	21
16	1	1	0	0	0	7,82	8,04	11,5	11,50	11,5	13	6	207	20
16	2	0	0	0	0	7,82	8,04	11,5	11,50	11,5	14	6	208	18
4	1	0	0	0	0	7,85	8,06	11,5	11,50	11,5	15	4	208	18
2	0	0	0	0	0	7,85	8,06	11,5	11,50	11,5	16	5	208	18

Figure 1 Sample of the source data used for predictive model building

The actual value of quality of an item is given in the column quality, where the values 1-6 correspond to good quality and values exceeding 6 to poor quality items. All remaining columns (with the exception of part_no – part number in batch) represent process monitoring parameters related to temperatures, chemical impurities in material, etc. All these variables are marked in Table 1 as Input, which indicates that they will be used as predictors.

Table 1 Variables in copper quality database and their role in the model building task

Variable	Type	Role
level_o2	Num	Input
part_no	Num	ID of product
quality	Num	Quality of product
size_max	Num	Input
size_min	Num	Input
sum_eddy_f1	Num	Input
sum_eddy_f2	Num	Input
sum_eddy_f3	Num	Input
sum_ferro_f1	Num	Input
sum_ferro_f2	Num	Input
sum_ferro_f3	Num	Input
Temp	Num	Input
vel_max	Num	Input
vel_mean	Num	Input
vel_min	Num	Input

The goal of quality assessment considered in this study is to classify manufactured items as either good or poor quality. Thus we will build a binary classifier, using as the target variable a binary equivalent of the quality variable (we denoted this qbin). The new variable qbin can be created by running the following SAS code:

```
data lab.copper_bin;
  set lab.copper_wire;
  if quality < 7 then qbin = 1;
  else qbin = 0;
run;
```

where the dataset copper_wire in the library lab contains the source data as shown in Figure 1 and Table 1, and copper_bin is the destination dataset with the column qbin appended. The code can be executed in SAS 9.2 (SAS Foundation).

The destination file copper_bin will be the basis for the predictive modelling task presented in the following section.

Building a Predictive Model in Enterprise Miner

This section presents how the data mining task outlined in the previous part can be solved using the SAS Enterprise Miner tool. Data mining tasks are solved in Enterprise Miner by building a process / data flow as illustrated in Figure 2. Development of the data processing flow is guided in Enterprise Miner by the SEMMA (Sample-Explore-Modify-Model-Assess) methodology. Following such methodology is recommended by data mining best practices in order to provide repeatable and robust models. SEMMA is considered the SAS-specific implementation of the Cross Industry Standard Process for Data Mining methodology (CRISP-DM).

This section is structured according to the SEMMA steps.

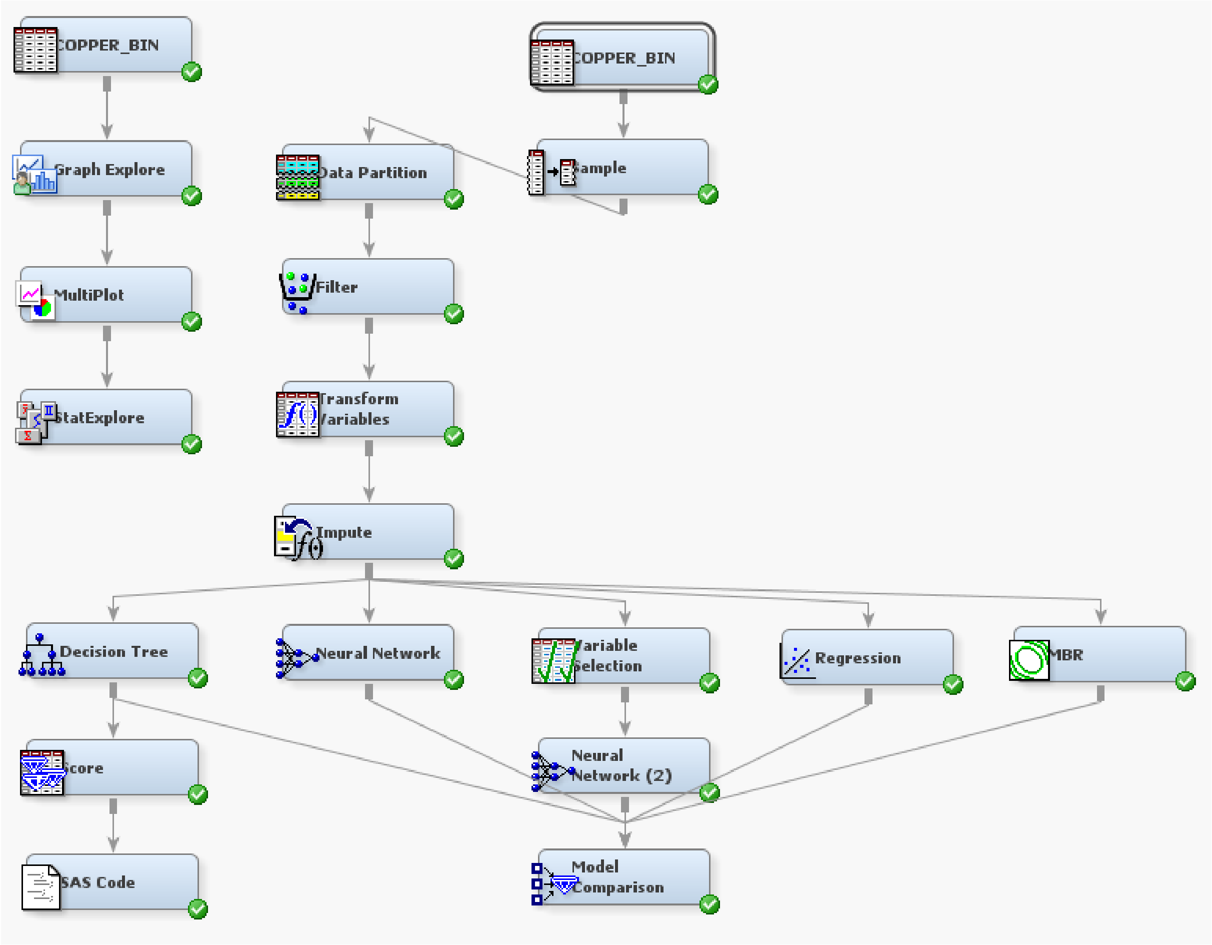


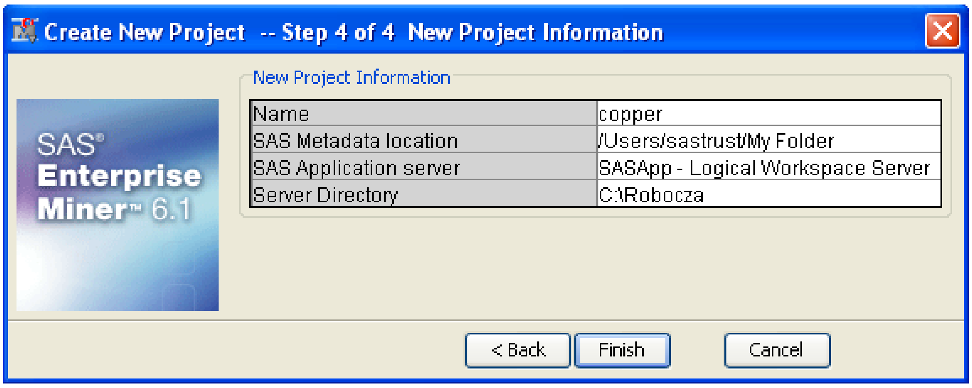
Figure 2 Overview of the EM process diagram created in this study

Preparatory tasks

Enterprise Miner is a project – oriented tool, so the first task is to create a new project for this study and to connect the source data to the project. Since all datasets are referenced in SAS through the means of libraries (i.e., LIBREFs which are references to folders / directories in the host operating system), a new library has to be created in the project to point to the location of the copper_bin source file.

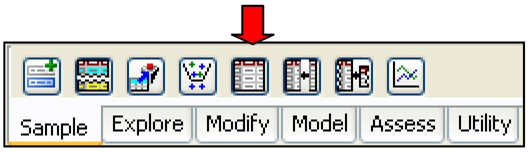
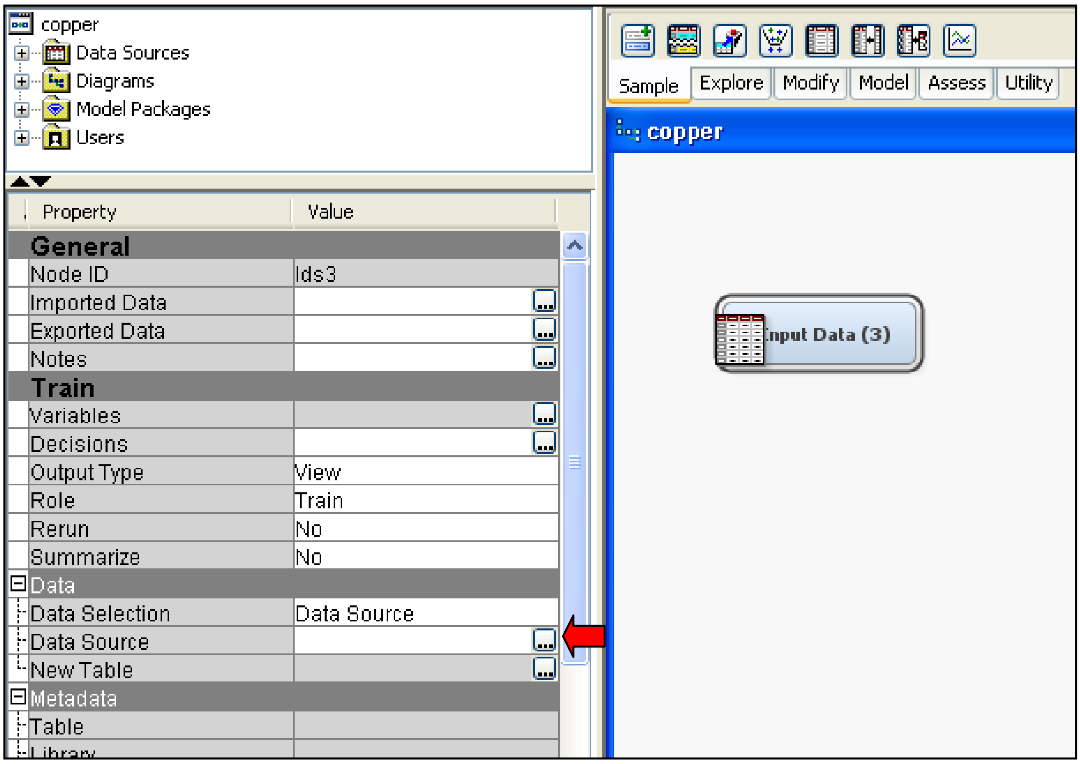
These tasks are realized in the following steps:

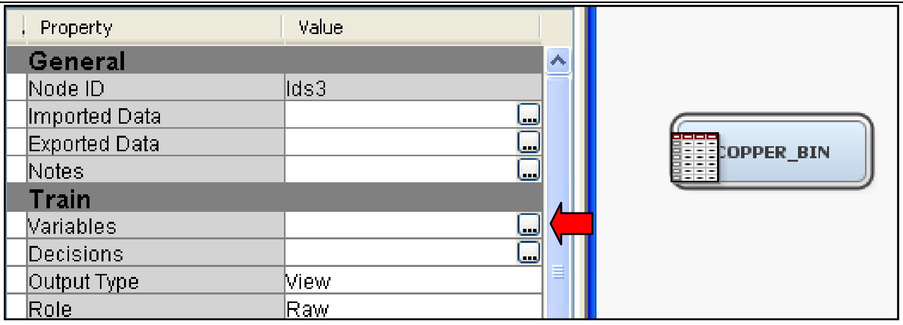
Task	Description
1	Create the new Project The project is created using the Project Wizard launched by the File-New-Project menu. In the wizard, the following three elements are specified: • SAS server for the project • Project name and SAS server directory • SAS Folder location where project metadata will be stored For the first and the third point the default values can be left. The project name and server directory in this example are: copper and C:\robocza, which gives the final setting for the new project as shown below.

	 Create New Project -- Step 4 of 4 New Project Information New Project Information Name copper SAS Metadata location /Users/sastrust/My Folder SAS Application server SASApp - Logical Workspace Server Server Directory C:\Robocza
2	Connect the source data to the project 1. Create the new Library The source data used in this example is the copper_bin dataset. First, a new library has to be created to point to the location (OS folder) of this dataset – the library is created using the Library Wizard launched by the File-New-Library menu. 2. Create the new Data Source data source is created using the Data Source Wizard (File-New-Data Source menu). In the wizard, the following decisions are made: • A SAS table is selected that becomes the data source (in this example the dataset copper_bin is used, found in the library created in the previous step) • The column metadata are defined (such as the roles in the model and measurement levels of variables). In this step default values of metadata can be left, as proposed by the Metadata Advisor. Although the metadata could be corrected here, this will be done and explained in detail in the Sample data step. • All other settings should be accepted as proposed by the wizard.
3	Create the new Diagram Using the File-New-Diagram menu, the new diagram called copper is created. The diagram will be populated with Enterprise Miner nodes to form the process flow as illustrated in Figure 2.

Sample data

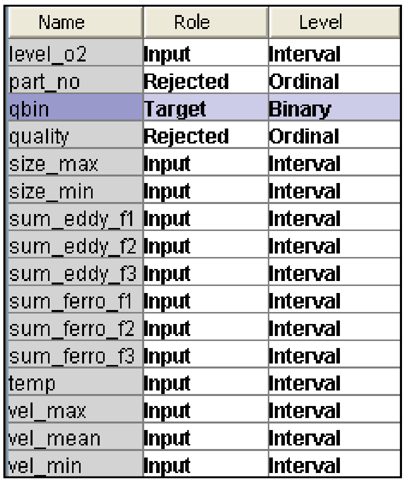
In this step, we start building the process flow by connecting to and possibly sampling the data source, providing proper metadata for the variables and partitioning the data into training, validation and testing layers. These tasks are done in the following steps.

Task	Description
1	Add to the diagram the Input Data node 1. Drag and drop onto the diagram pane the Input Data node found on the Sample toolbar.  2. Next, select the Input Data node and specify the data source that the node connects to (using the Data Source editor in the node's Property pane). Select the copper_bin data source.  copper Data Sources Diagrams Model Packages Users Sample Explore Modify Model Assess Utility copper Input Data (3) Property: Value General Node ID: Ids3 Imported Data Exported Data Notes Train Variables Decisions Output Type: View Role: Train Rerun: No Summarize: No Data Data Selection: Data Source Data Source New Table Metadata Table Library
2	Setup metadata for the data source Prior to building a predictive model, variables must be properly described by metadata to indicate (a) the intended role of a variable in the process (target or predictor variable), and (b) the measurement level of a variable (as quantitative or class variable). Metadata pertaining to variables are setup using the Variables editor (available in the Input Data property pane), as shown below.



Property	Value
General	
Node ID	Ids3
Imported Data	...
Exported Data	...
Notes	...
Train	
Variables	...
Decisions	...
Output Type	View
Role	Raw

The role and measurement level of the copper_bin variables should be specified as follows. The qbin variable is used as the *binary target*, the part number and original value of quality variables are *rejected* from model building and all other variables are used as predictors with the *interval* measurement level (which indicates a quantitative variable).

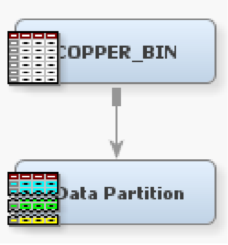
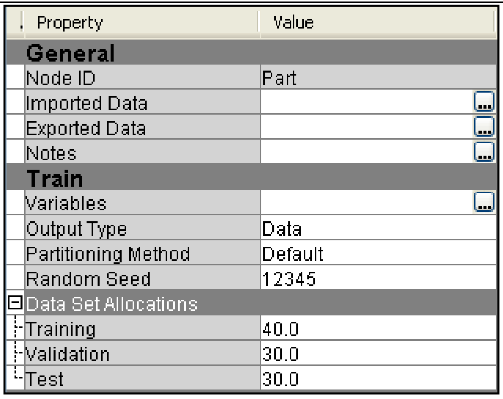


Name	Role	Level
level_o2	Input	Interval
part_no	Rejected	Ordinal
qbin	Target	Binary
quality	Rejected	Ordinal
size_max	Input	Interval
size_min	Input	Interval
sum_eddy_f1	Input	Interval
sum_eddy_f2	Input	Interval
sum_eddy_f3	Input	Interval
sum_ferro_f1	Input	Interval
sum_ferro_f2	Input	Interval
sum_ferro_f3	Input	Interval
temp	Input	Interval
vel_max	Input	Interval
vel_mean	Input	Interval
vel_min	Input	Interval

3 Partition data

Prior to training predictive models, input data must be divided into *training*, *validation* and *test* partitions. The training partition is used to fit a predictive model to the data, the validation partition is used to fine-tune parameters of the model in order to avoid model *overfitting* Model fine-tuning consists in modification of such parameters of models as depth of a decision tree or the number of perceptrons in the hidden layer of a neural net, etc. The test partition can then be used to estimate the expected prediction error for new data.

The data is split by connecting the Data Partition node (available in the Sample toolbox) as shown below.
Data Set Allocations property of the Data Partition node provides the size of partitions (as percentages of original data); default size can be left as is. The Exported Data property provides names of the training, validation and test datasets produced by the node.

Property	Value
General	
Node ID	Part
Imported Data	...
Exported Data	...
Notes	...
Train	
Variables	...
Output Type	Data
Partitioning Method	Default
Random Seed	12345
⊟Data Set Allocations	
Training	40.0
Validation	30.0
Test	30.0

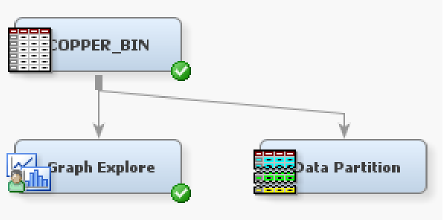
Explore data

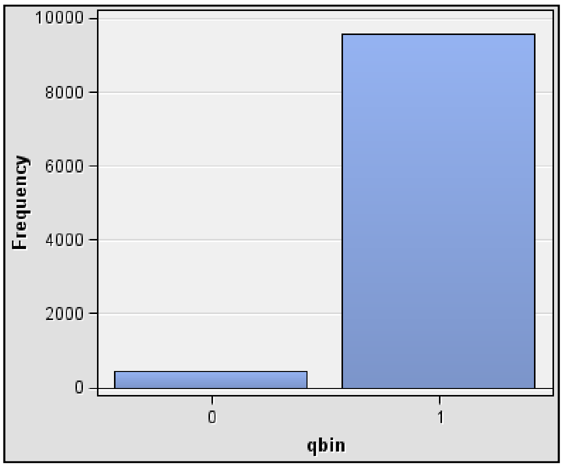
The purpose of this step is to discover important characteristics of distributions of variables as well as inconsistencies, errors and outliers in data. Based on these findings, required data modifications can be designed in order to clean the data, impute missing values or transform variables to make some distributions less skewed or more normal-like (e.g., by the log transformation). These steps are mandatory to ensure robust predictive models.

In this guide we focus on some Enterprise Miner tools for graphical exploration and for statistical analysis of data, such as:

- Graph Explore,
- MultiPlot,
- StatExplore.

These tools can be used as shown and explained in the following steps.

Task	Description
1	Perform graphical exploration of data **Using the Graph Explore tool**  1. Drag the Graph Explore icon into the diagram and connect to the Input Data node (the tool can be found in the Explore toolbar). 2. Run the tool (right click – Run menu). 3. Open Results window. Using View-Plot menu of Results window open the Chart wizard to configure a relevant graphical summary of data. The first observation we make is that the data are heavily *unbalanced* in terms of distribution of the target variable. The proportion of observations is about 95% vs 5% of good quality (qbin=1) and poor quality (qbin=0) items, respectively.

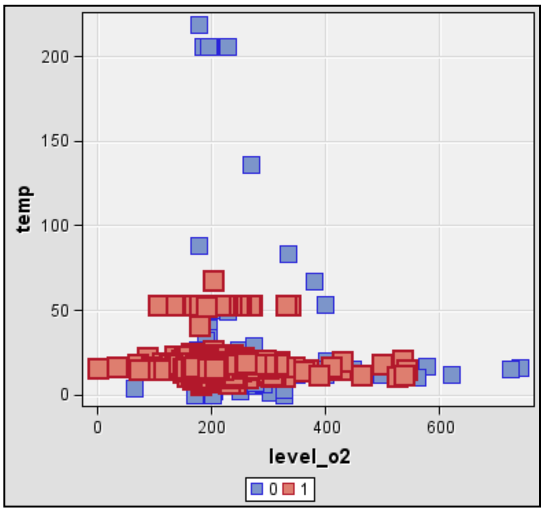


Building predictive models based on such data is generally difficult, as machine learning algorithms tend to bias the models towards accurate prediction of the majority class (qbin=1), with poor predictive performance of the rare class (qbin=0). To avoid this, several techniques will be discussed later in this guide, including oversampling representatives of the rare class.

The Graph Explore tool provides features for graphical analysis of distributions of predictors and mutual relationships of predictors. These include several types of statistical plots (density plot, boxplots etc.) as well as many types of interactive explanatory plots (such as 2D and 3D plot scatter plots, contour plots etc.)

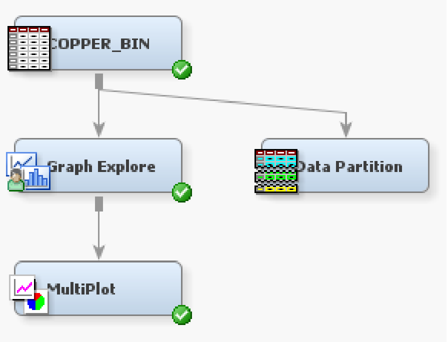
An example of a Scatter Chart is shown below, illustrating the relationship between the variables level_o2 and temp, grouped by the target variable (qbin).

It can be observed from this plot that the upper tails of distributions of these two predictors correspond to poor quality items (qbin=0). This is an important finding, also confirmed for other predictors, as counter - outlier techniques usually tend to remove these tails. In our study, we will use these techniques cautiously so as not to lose some significant portion of the rare class representatives from the training data.



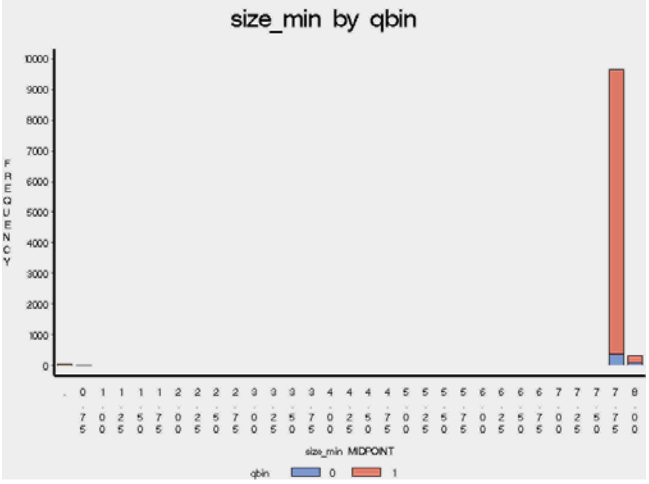
It should be noticed that all charts created in the Graph Explore tool are interactive, i.e., by selecting an element on the plot (such as a point or group of points in scatter plot, a bin in the histogram etc.), corresponding observations in the tabular view of raw data are also selected. This allows for easy and efficient analysis of observations which contribute to untypical values in distributions of some variables.

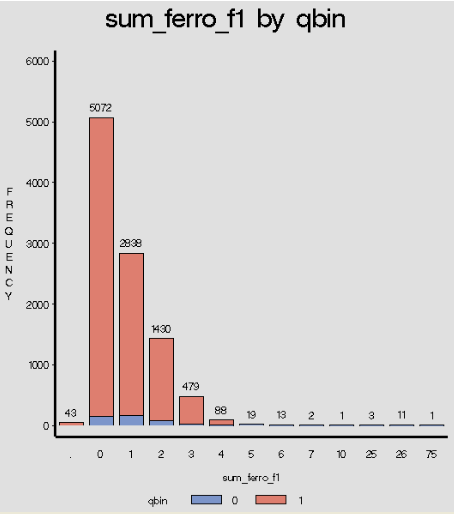
Graphical exploration using the Multiplot tool



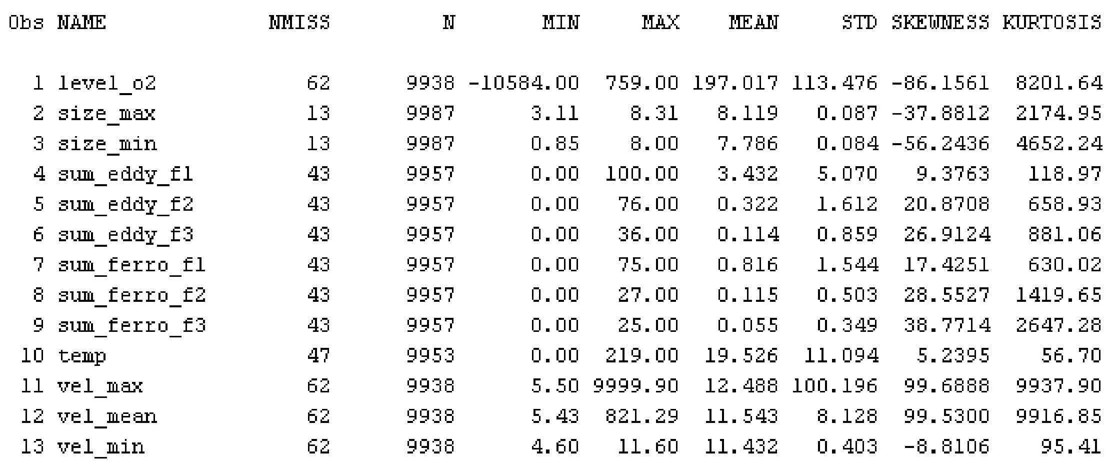
To use this tool, connect its icon as shown in the diagram and Run the analysis (right click menu).
In the Results window, maximize the Train Graphs window to start quick, interactive inspection of distributions of subsequent variables. In this way we can efficiently scan through large data volumes to reveal illegal values / errors /outliers. An example of such analysis is shown below, where very small values of the size_min variable are immediately detected in the histogram below. Such erroneous observations will have to be filtered off in the Modify step.

We also observe that some variables have very skewed distributions (such as sum_ferro_f1, shown below). These variables can be later transformed to make the distribution more symmetric, which improves performance of regression or discriminant analysis methods.





Another interesting summary obtained from the Multiplot results window are descriptive statistics calculated for all interval variables (shown below). This result provides a number of hints related to required transformations of data.



```
Obs NAME            NMISS       N       MIN     MAX    MEAN     STD SKEWNESS KURTOSIS

  1 level_o2           62    9938 -10584.00  759.00 197.017 113.476 -86.1561  8201.64
  2 size_max           13    9987      3.11    8.31   8.119   0.087 -37.8812  2174.95
  3 size_min           13    9987      0.85    8.00   7.786   0.084 -56.2436  4652.24
  4 sum_eddy_f1        43    9957      0.00  100.00   3.432   5.070   9.3763   118.97
  5 sum_eddy_f2        43    9957      0.00   76.00   0.322   1.612  20.8708   658.93
  6 sum_eddy_f3        43    9957      0.00   36.00   0.114   0.859  26.9124   881.06
  7 sum_ferro_f1       43    9957      0.00   75.00   0.816   1.544  17.4251   630.02
  8 sum_ferro_f2       43    9957      0.00   27.00   0.115   0.503  28.5527  1419.65
  9 sum_ferro_f3       43    9957      0.00   25.00   0.055   0.349  38.7714  2647.28
 10 temp               47    9953      0.00  219.00  19.526  11.094   5.2395    56.70
 11 vel_max            62    9938      5.50 9999.90  12.488 100.196  99.6888  9937.90
 12 vel_mean           62    9938      5.43  821.29  11.543   8.128  99.5300  9916.85
 13 vel_min            62    9938      4.60   11.60  11.432   0.403  -8.8106    95.41
```

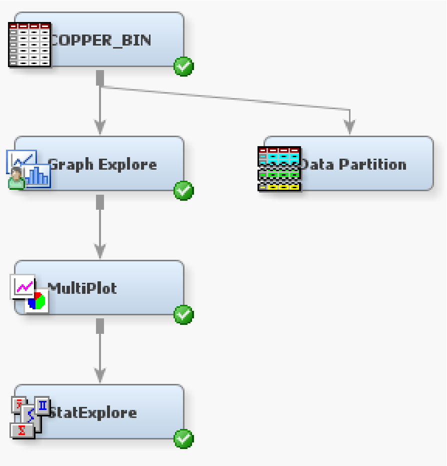
The following observations can be made:

- Some observations have very small or very high MIN or MAX values as compared to the mean value (e.g., level_o2 with erroneous MIN value, or vel_max and vel_mean with erroneous MAX value),
- Some observations have very large standard deviation as compared with the mean,
- All variables contain missing values (the number of missing values is given in the NMISS column).

Based on these observations, required data filtering and transformation rules will be implemented in the next SEMMA step.

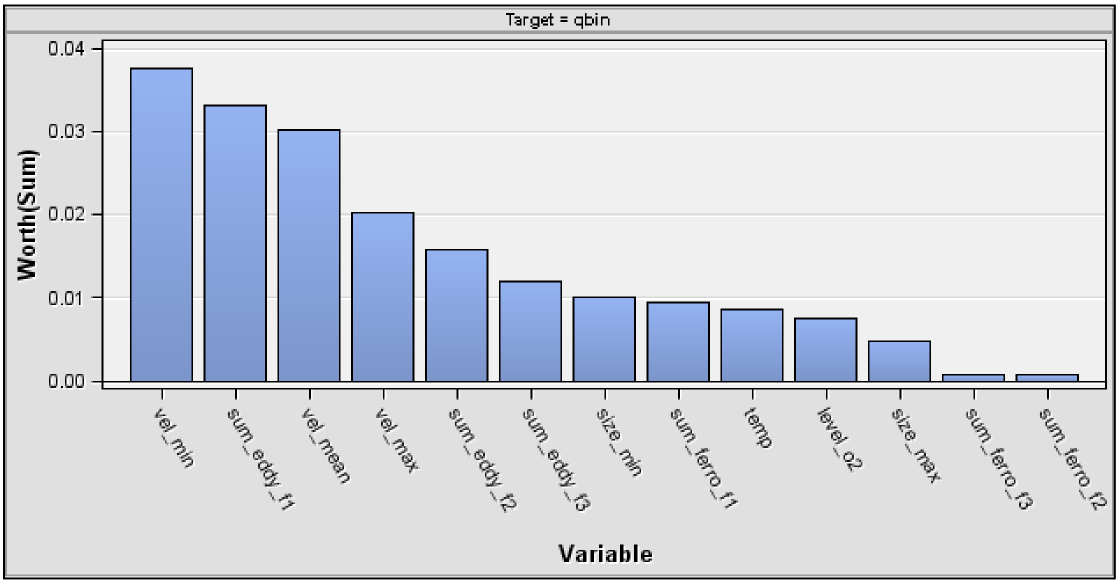
2 Perform statistical analysis of data – using the StatExplore tool

The StatExplore tool allows to examine distributions of variables and analyze association of inputs with the (interval or class) target. Based on these analyses, variable selection can be realized in order to reduce dimensionality of predictive (or clustering) models.

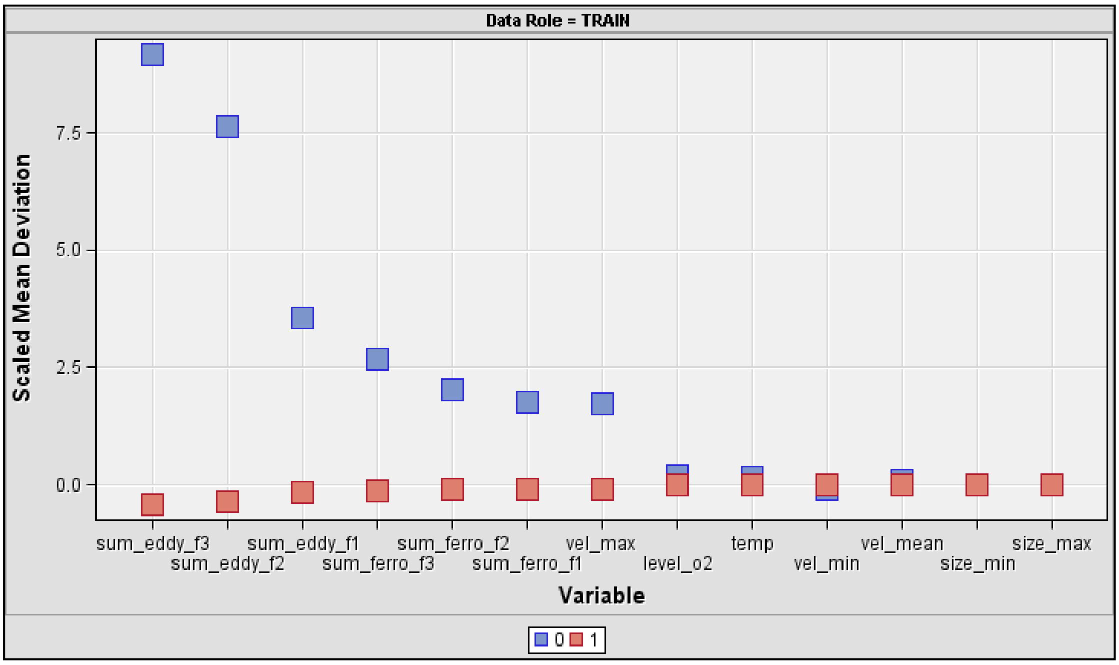


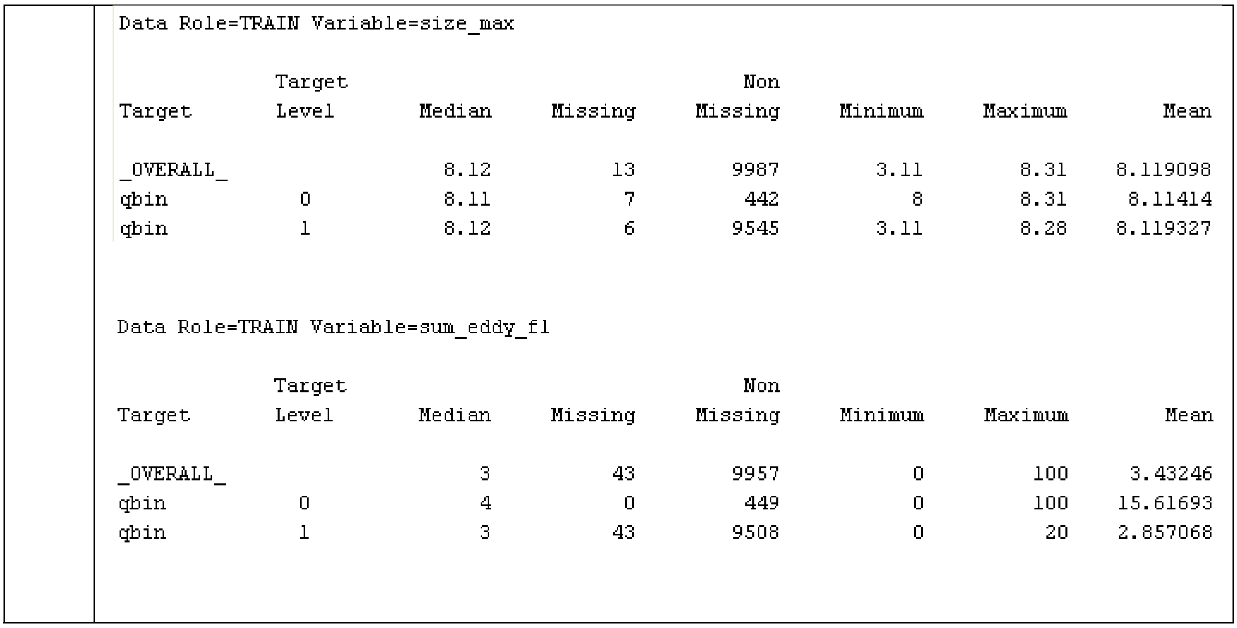
The StatExplore tool should be connected as shown in the diagram and executed (right click Run menu).
In the Results window, the Variable Worth and Interval Variables : qbin charts are available (through the View-Plot menu of the Results window).

The Variable Worth chart (shown below) ranks variables by their importance for target prediction, as calculated by the decision tree algorithm.



Association of variables with the target is also shown in the following Scaled Mean Deviation plot. Here the (scaled) means in the “target=0” and “target=1” groups are compared with the overall mean of the variable (represented by the level of zero). This plot corresponds with the per-group descriptive statistics shown next. For instance, the variable size_max realizes roughly the same mean value in the groups “qbin=1”, “qbin=0” and overall, hence its position on the right of the plot. On the other hand, the variable sum_eddy_f1 realizes similar mean value in the group “qbin=1” and overall, with much bigger mean in the “qbin=0” groups, which is clearly seen in the Mean Deviation chart.





```
Data Role=TRAIN Variable=size_max

               Target                                Non
Target         Level       Median      Missing     Missing     Minimum     Maximum        Mean

_OVERALL_                    8.12           13        9987        3.11        8.31    8.119098
qbin             0           8.11            7         442           8        8.31     8.11414
qbin             1           8.12            6        9545        3.11        8.28    8.119327


Data Role=TRAIN Variable=sum_eddy_fl

               Target                                Non
Target         Level       Median      Missing     Missing     Minimum     Maximum        Mean

_OVERALL_                       3           43        9957           0         100     3.43246
qbin             0              4            0         449           0         100    15.61693
qbin             1              3           43        9508           0          20    2.857068
```

Summarizing, the following conclusions can be drawn from the Explore step:

- The data has heavily imbalanced distribution of target with roughly 5% of the rare class (poor quality items),
- Some predictors have clearly erroneous observations (such as the negative value of the level_o2), most of predictors have skewed distributions,
- Most of predictors include outlying observations, these however should be removed with caution (i.e., only when the value of predictor is beyond physical range of the variable), as outliers generally correspond to the rare class (poor quality) observations.

These issues will be tackled in the following Modify and Model steps.

Modify data

The purpose of this step is to:

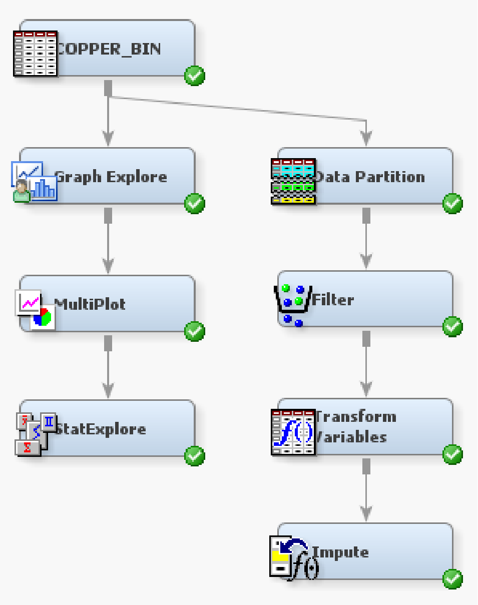
- Remove observations with wrong or outlying values of input variables,
- Transform variables to reduce skewness in distribution,
- Impute missing values.

Transformations of data to reduce skew in distribution bring variables closer to the normal distribution, which improves performance of predictive models based on the assumption on normality of features (such as the LDA). Filling in missing data (e.g., based on values in similar observations or using more sophisticated approach, such as prediction based methods) may improve performance of regression methods or neural classifiers which otherwise ignore observations in which missing values occur. (Note that decision tree algorithms accept missing values as legitimate values of predictors).

In this guide, we demonstrate several features of Enterprise Miner used to modify data, such as features implemented in the following nodes:

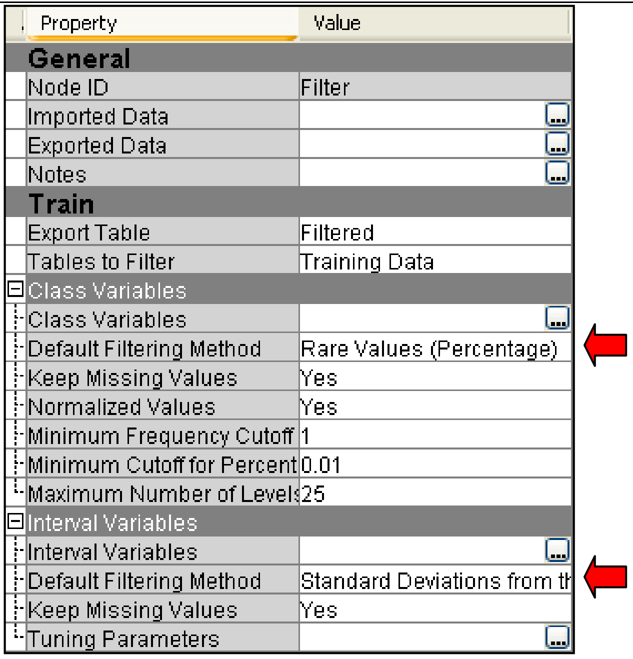
- Filter,
- Transform Variables,
- Impose.

The nodes should be connected to the Input Data as shown in the diagram below.



Data transformations implemented with these nodes are outlined in the following procedure.

Task	Description
1	Filter observations containing erroneous inputs 1. Select the Filer node, which activates the node's Property window as shown below. 2. In the Property window, setup conditions for filtering out observations, based on values of class variables and interval variables. In this example, we change the Default Filtering Method for both class and interval variables to None (as these apply to all variables), and define specific filtering conditions for individual variables.

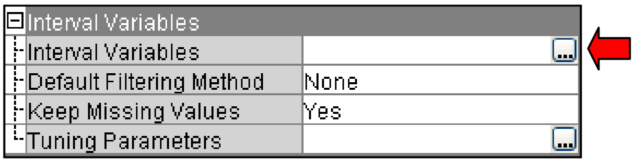


Property	Value
General	
Node ID	Filter
Imported Data	...
Exported Data	...
Notes	...
Train	
Export Table	Filtered
Tables to Filter	Training Data
⊟ Class Variables	
Class Variables	...
Default Filtering Method	Rare Values (Percentage)
Keep Missing Values	Yes
Normalized Values	Yes
Minimum Frequency Cutoff	1
Minimum Cutoff for Percent	0.01
Maximum Number of Levels	25
⊟ Interval Variables	
Interval Variables	...
Default Filtering Method	Standard Deviations from th
Keep Missing Values	Yes
Tuning Parameters	...

The tool offers several filtering methods, e.g., Standard Deviations from the Mean for interval variables. This method removes outliers, where outliers are defined by the 3 standard deviations from the mean condition.

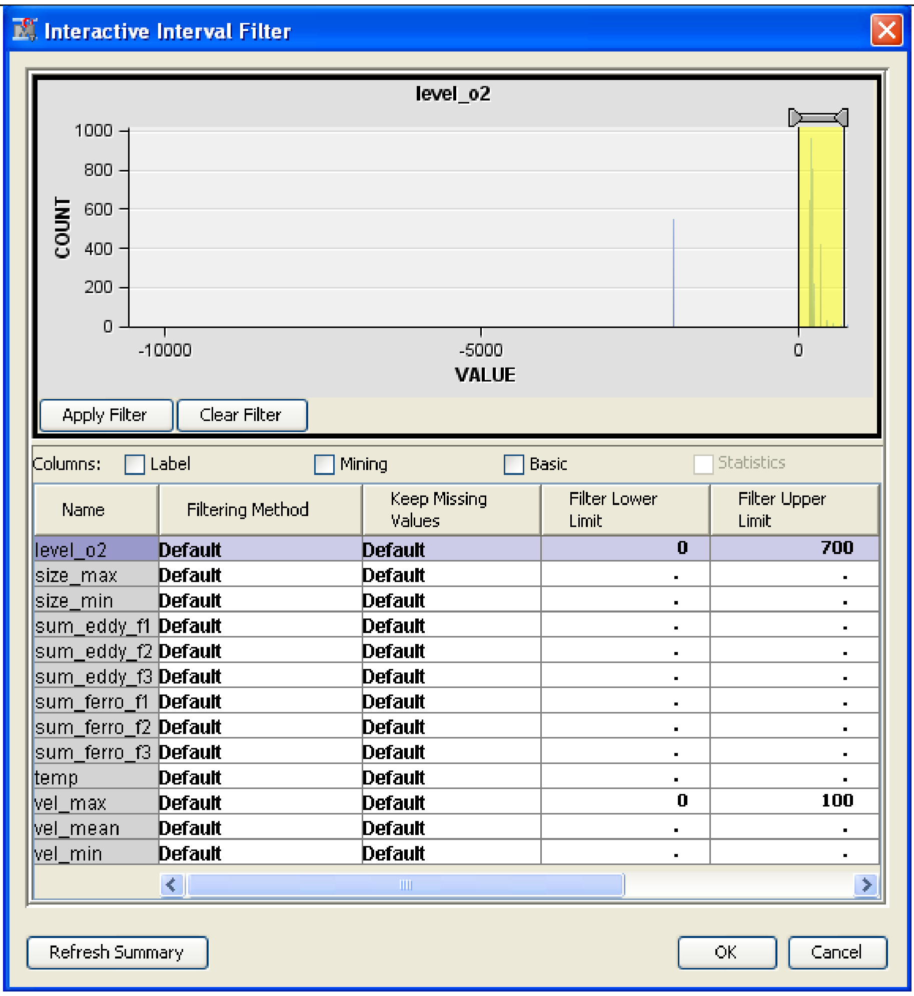
In this example, we switch the Default Filtering Method to None. The default Standard Deviations from the Mean method would remove too many rare case (qbin=0) observations, as these observations are generally overrepresented in the far ends of distributions of predictors, as shown in the Explore stage. Thus we manually setup filtering conditions to remove wrong and preserve feasible albeit outlying data.

We do this using the editor of filtering conditions for interval inputs (the editor is invoked as indicated by the arrow below).



⊟ Interval Variables	
Interval Variables	...
Default Filtering Method	None
Keep Missing Values	Yes
Tuning Parameters	...

Next, we specify lower and upper limits for the inputs: level_o2 and vel_max as shown below (this removes observations with erroneous values in these variables).

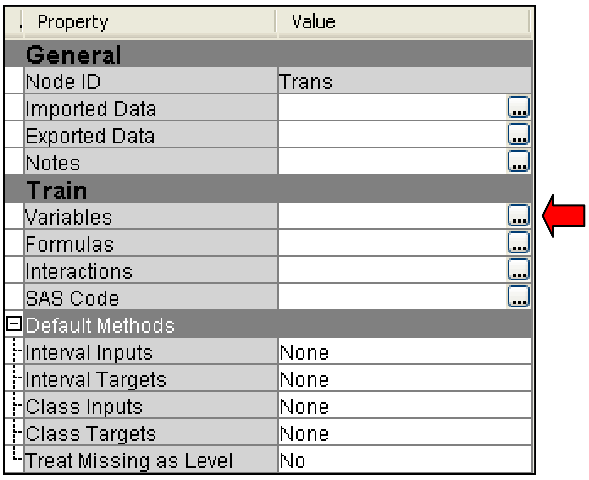


Columns: □ Label □ Mining □ Basic □ Statistics

Name	Filtering Method	Keep Missing Values	Filter Lower Limit	Filter Upper Limit
level_o2	Default	Default	0	700
size_max	Default	Default	.	.
size_min	Default	Default	.	.
sum_eddy_f1	Default	Default	.	.
sum_eddy_f2	Default	Default	.	.
sum_eddy_f3	Default	Default	.	.
sum_ferro_f1	Default	Default	.	.
sum_ferro_f2	Default	Default	.	.
sum_ferro_f3	Default	Default	.	.
temp	Default	Default	.	.
vel_max	Default	Default	0	100
vel_mean	Default	Default	.	.
vel_min	Default	Default	.	.

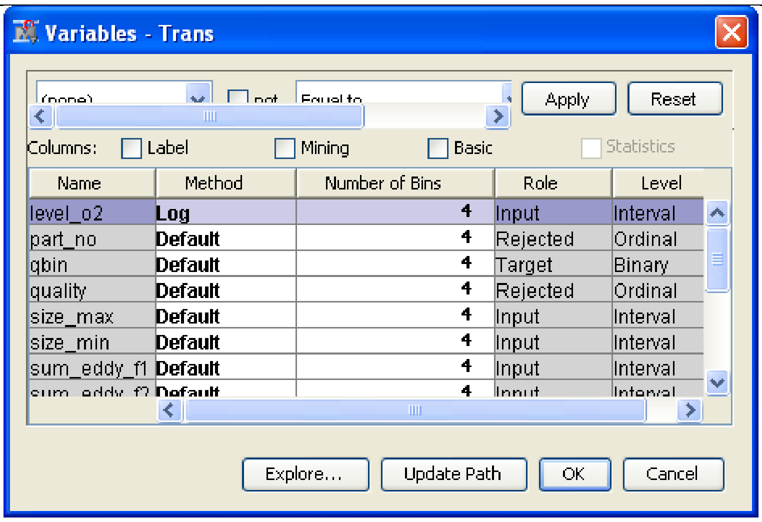
2 Transform input variables to reduce skewness in distribution

1. Select the Transform Variables node, this activates the node's Property window as shown below.
2. Open the transformations editor (as indicated by the arrow).



Property	Value
General	
Node ID	Trans
Imported Data	...
Exported Data	...
Notes	...
Train	
Variables	...
Formulas	...
Interactions	...
SAS Code	...
⊟ Default Methods	
Interval Inputs	None
Interval Targets	None
Class Inputs	None
Class Targets	None
Treat Missing as Level	No

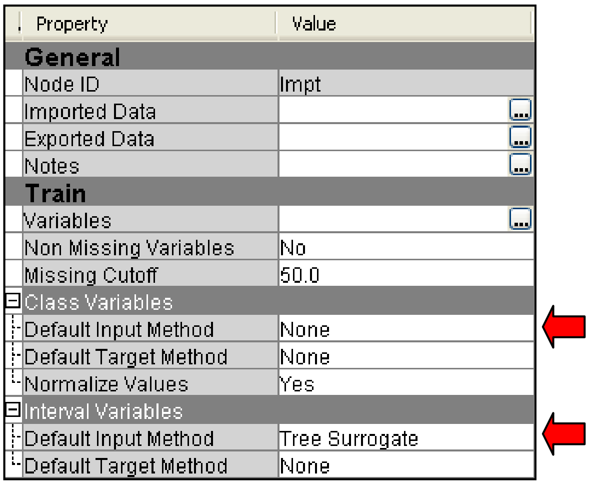
In this example, we will apply the log transformation to the level_o2 input, as shown in the Method column of the transformations editor.



Name	Method	Number of Bins	Role	Level
level_o2	**Log**	4	Input	Interval
part_no	**Default**	4	Rejected	Ordinal
qbin	**Default**	4	Target	Binary
quality	**Default**	4	Rejected	Ordinal
size_max	**Default**	4	Input	Interval
size_min	**Default**	4	Input	Interval
sum_eddy_f1	**Default**	4	Input	Interval
sum_eddy_f2	**Default**	4	Input	Interval

3 Impute missing values

1. Select the Impute node, which activates the node’s Property window as shown below.
2. Change the imputation method for class variables to None and for interval variables to Tree Surrogate, as shown below.

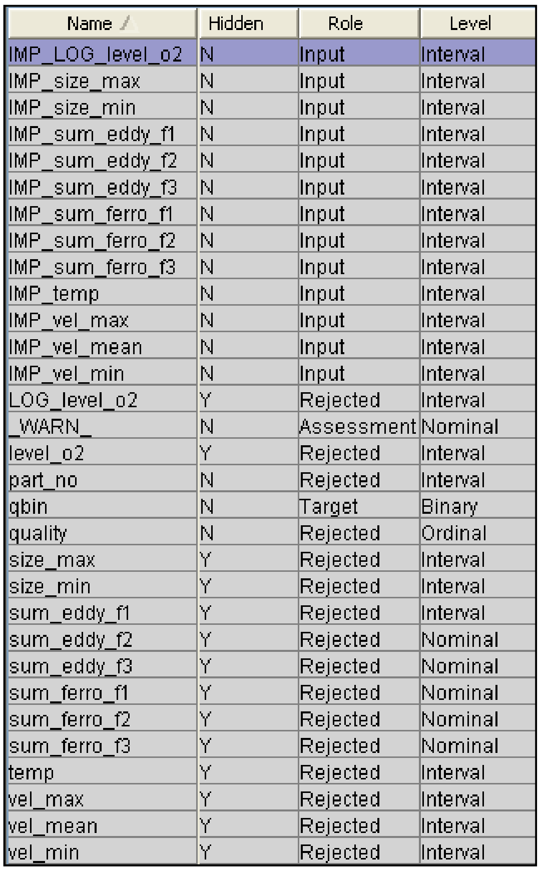


Property	Value
General	
Node ID	Impt
Imported Data	...
Exported Data	...
Notes	...
Train	
Variables	...
Non Missing Variables	No
Missing Cutoff	50.0
⊟ Class Variables	
Default Input Method	None
Default Target Method	None
Normalize Values	Yes
⊟ Interval Variables	
Default Input Method	Tree Surrogate
Default Target Method	None

There are several methods of missing value imputation, such as simple methods which fill in the mean or median of the variable’s distribution, or more sophisticated methods such as the ones based on robust M-estimators of distribution location parameter, etc.
In this example, we use the tree based imputation method which calculates the missing value as predicted by the remaining inputs (for the purpose of this analysis, the variable with missing values is regarded as the target).

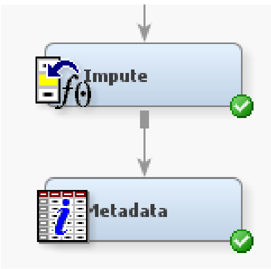
We note that data transformation and missing value imputation nodes in Enterprise Miner do not override the original variables. Instead they add new variables to the dataset, with names based on the type of transformation, as shown in the metadata listing below.

E.g., the level_o2 variable was first logged to create the new LOG_level_o2 variable, which was later transformed with the Impute node to create the IMP_LOG_level_o2 variable. The ‘old’ variables are rejected from analysis and the modified variables labeled as inputs, i.e., will be used as predictors (this is done by the Role metadata column).



Name	Hidden	Role	Level
IMP_LOG_level_o2	N	Input	Interval
IMP_size_max	N	Input	Interval
IMP_size_min	N	Input	Interval
IMP_sum_eddy_f1	N	Input	Interval
IMP_sum_eddy_f2	N	Input	Interval
IMP_sum_eddy_f3	N	Input	Interval
IMP_sum_ferro_f1	N	Input	Interval
IMP_sum_ferro_f2	N	Input	Interval
IMP_sum_ferro_f3	N	Input	Interval
IMP_temp	N	Input	Interval
IMP_vel_max	N	Input	Interval
IMP_vel_mean	N	Input	Interval
IMP_vel_min	N	Input	Interval
LOG_level_o2	Y	Rejected	Interval
WARN	N	Assessment	Nominal
level_o2	Y	Rejected	Interval
part_no	N	Rejected	Interval
qbin	N	Target	Binary
quality	N	Rejected	Ordinal
size_max	Y	Rejected	Interval
size_min	Y	Rejected	Interval
sum_eddy_f1	Y	Rejected	Interval
sum_eddy_f2	Y	Rejected	Nominal
sum_eddy_f3	Y	Rejected	Nominal
sum_ferro_f1	Y	Rejected	Nominal
sum_ferro_f2	Y	Rejected	Nominal
sum_ferro_f3	Y	Rejected	Nominal
temp	Y	Rejected	Interval
vel_max	Y	Rejected	Interval
vel_mean	Y	Rejected	Interval
vel_min	Y	Rejected	Interval

The metadata can be inspected and modified if necessary using the Metadata node as shown in the diagram below. This node could be used for manual feature selection, i.e., to include or reject variables based on association of inputs with the target (see results of the StatExplore node).



In this example we use the Metadata node only for illustration on how transformation nodes work and hence this node will not be shown in the following diagrams.

Build predictive models

In this step, we will build different predictive models to estimate the target, i.e., to classify the manufactured items as good or poor quality. We will try:

- Decision trees,
- Neural networks,
- Logistic regression,

- Memory based reasoning method (i.e., the nonparametric k nearest neighbours classifier).

We will also demonstrate how feature selection can be realized in Enterprise Miner. Strictly speaking, this step is not crucial in our study, since the number of variables is relatively small. However in many real life problems with hundreds or more features, feature selection reducing dimensionality of data is mandatory, since many noisy features lead to deterioration in model performance and increase processing time and memory requirements.

Another important issue to consider prior to fitting a predictive model is definition of the criterion for model selection / comparison. By default, predictive models attempt to minimize the overall misclassification rate. This does not necessarily guarantee the optimal performance, especially if the consequences (costs) of the 0→1 and 1→0 misclassification decisions are different. In such studies, minimization of misclassification costs (or alternatively maximization of profits) might be the right criterion for model selection. This issue is discussed in the next section on Target profiling.

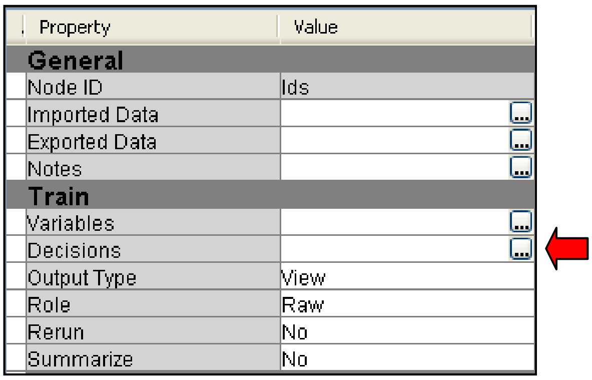
In this study, we also have to consider the problem of *highly imbalanced* data (as the poor quality class is represented by only ca 5% of observations). Predictive models usually demonstrate poor performance for the rare class. The reasons for this and the methods to tackle the problem are discussed in the Working with imbalanced data section.

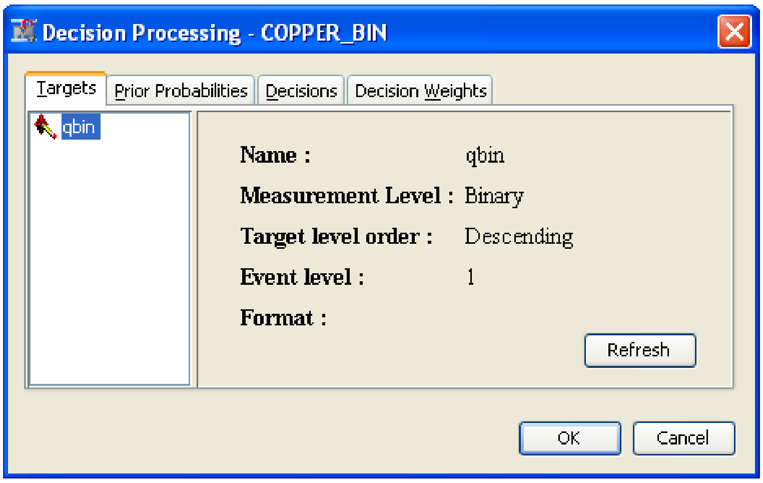
Target profiling

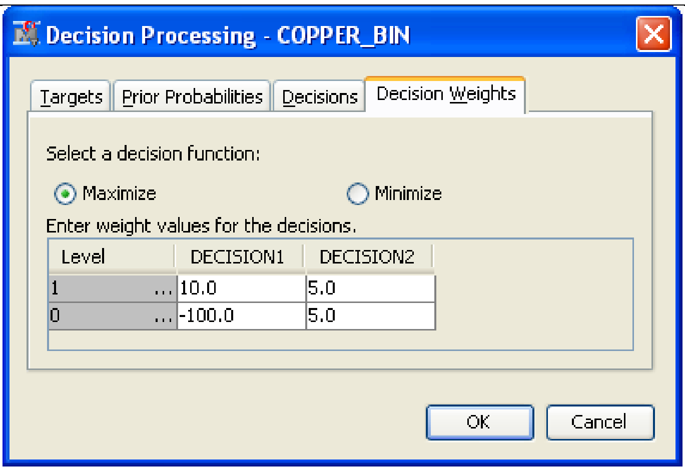
The target profile is used to specify costs of 0→1 and 1→0 misclassifications. Target profiles are also applied in non binary classification problems, when costs of c_i → c_j decisions are provided in the form of the cost matrix, with c_i, c_j denoting the class labels.

Once defined for the target variable, the target profile is used by the model fitting algorithms to attempt to minimize the misclassification costs or maximize the overall profit.

The target profile is setup using the procedure outlined below.

Task	Description
1	Associate the Target profile with the qbin variable 1. Select the Input Data node, which activates the node's Property window. 2. In the Property window, open the Decisions editor as shown below. In the Decision Processing window, click the Build button, which creates the default target profile for the qbin variable.  Property: Value General Node ID: Ids Imported Data Exported Data Notes Train Variables Decisions Output Type: View Role: Raw Rerun: No Summarize: No

	3. The target *event level* is selected based on the target level order. The target event level is later used to define the meaning of *sensitivity* of the classifier; also the (logit of) probability modelled by the logistic regression is related to the target event. In our case, we accept the event level of 1 (which translates into the decision of the classifier that an item is of good quality; also sensitivity of the model, reported later in the "Assessment of performance of the models" section will denote probability of correct recognition of the good quality item). (If event level of 0 makes interpretation of classifier's decisions easier, the event level can be changed by setting the Target level order to Ascending in the metadata associated with the target variable. Generally, the event level is selected as the first value in the list of sorted values of the target).  Decision Processing - COPPER_BIN Targets Prior Probabilities Decisions Decision Weights qbin Refresh OK Cancel Name : qbin Measurement Level : Binary Target level order : Descending Event level : 1 Format :
2	Define decision weights In Decision Weights editor (shown in the following picture), we specify costs (or profits) associated with particular decisions by the classifier, where: • DECISION1 means classify as good quality (qbin=1), • DECISION2 means classify as poor quality (qbin=0), as indicated by the Decision tab (see the second picture). In the weights (or profits) matrix shown below, we reflect the following scenario (this scenario is based on the actual business perspective as seen by the copper company, albeit the values of profits/costs are fictitious): • If an actually good quality item (level=1) is classified as good quality (DECISION1), then the company makes the profit of 10. • If an actually poor quality item (level=0) is classified as good quality (DECISION1), then the company makes the profit of -100 (i.e., makes a loss, due to having to pay high warranty costs to its customer, exceeding prior profits). • If an item is classified as poor quality (DECISION2), then the company sells the product as second quality, thus cheaper, and makes the profit of 5, irrespective of the actual quality.



Decision Processing - COPPER_BIN

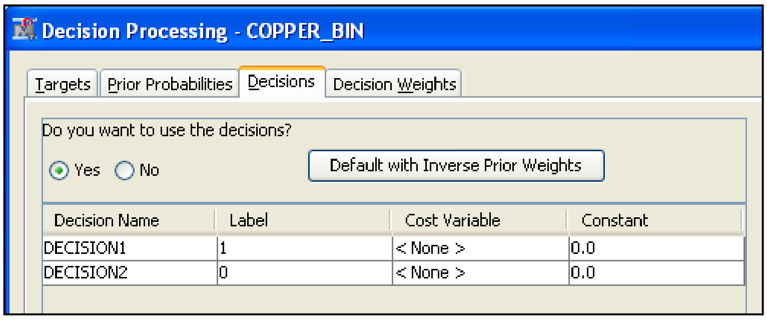
Select a decision function:

● Maximize ○ Minimize

Enter weight values for the decisions.

Level	DECISION1	DECISION2
1 ...	10.0	5.0
0 ...	-100.0	5.0

We select the *maximize* decision function which is consistent with our interpretation of the values entered as profits (if costs were entered, then the *minimize* decision function would have to be selected).



Decision Processing - COPPER_BIN

Do you want to use the decisions?

● Yes ○ No

Decision Name	Label	Cost Variable	Constant
DECISION1	1	< None >	0.0
DECISION2	0	< None >	0.0

Once the target profile and the weights matrix is associated with the target, subsequent builds of predictive models will attempt to maximize the profit (or minimize costs) as the criterion for classifier selection.

Working with imbalanced data

If members of one class are rare in the training data (as the poor quality qbin=0 items are in our study), then classifiers usually perform poorly for this class. The following reasons make detection of rare cases challenging:

- *A priori* probability Pr(c_1) of the rare class (denoted c_1) is small, as compared with *a priori* probabilities of remaining classes. Since the *a posteriori* (or posterior) probability of this class is proportional to its *a priori* probability: $Pr(c_1|x) \sim Pr(x|c_1)Pr(c_1)$, where x denotes the vector of features of an item to classify, then it may be hard to find items x for which Pr(c_1|x) wins among all classes.
- Iterative machine learning algorithms (such as neural nets) tend to fine-tune the weights towards good recognition of the frequent class. The rules for recognition of the rare class tend to become very weak as training examples for this class are presented infrequently to the weights modification algorithm.

For these reasons, working with imbalanced data requires special techniques to improve detection of the rare cases.

In this guide we demonstrate two techniques that are feasible in Enterprise Miner:

- Data oversampling: an artificial training dataset is constructed where the rare cases are oversampled so that frequencies of the classes are balanced. Obviously, performance of predictive models is later measured based on the original (i.e., imbalanced) proportions of classes.
- Boosting recognition of the rare class by the means of decision weights matrix. For instance, if the classifier tends to classify many poor quality items (level qbin=0) as good quality (DECISION1), then we may make the classifier avoid the 0→1 misclassification by applying a high cost of this decision. In this way, we can favour the "pro rare case" decisions which will boost specificity of models.

  Note that this approach is based on the same Decision Weights matrix as used before in the Target profiling section. However, decision weights defined previously were supposed to reflect the actual consequences of wrong and correct decisions. Here decision weights are simply the means to boost recognition of the otherwise "neglected" class.

In this study, we will start with the second approach, as the previously specified Decision Weights matrix works against the wrong, although likely, 0→1 decisions. This should improve recognition of the poor quality items. We will verify this supposition by comparing the classifier built using the decision weights matrix with the original one trained to minimize the overall misclassification rate.

Later in this study, we will also attempt the first method, i.e., we will retrain models based on oversampled data.

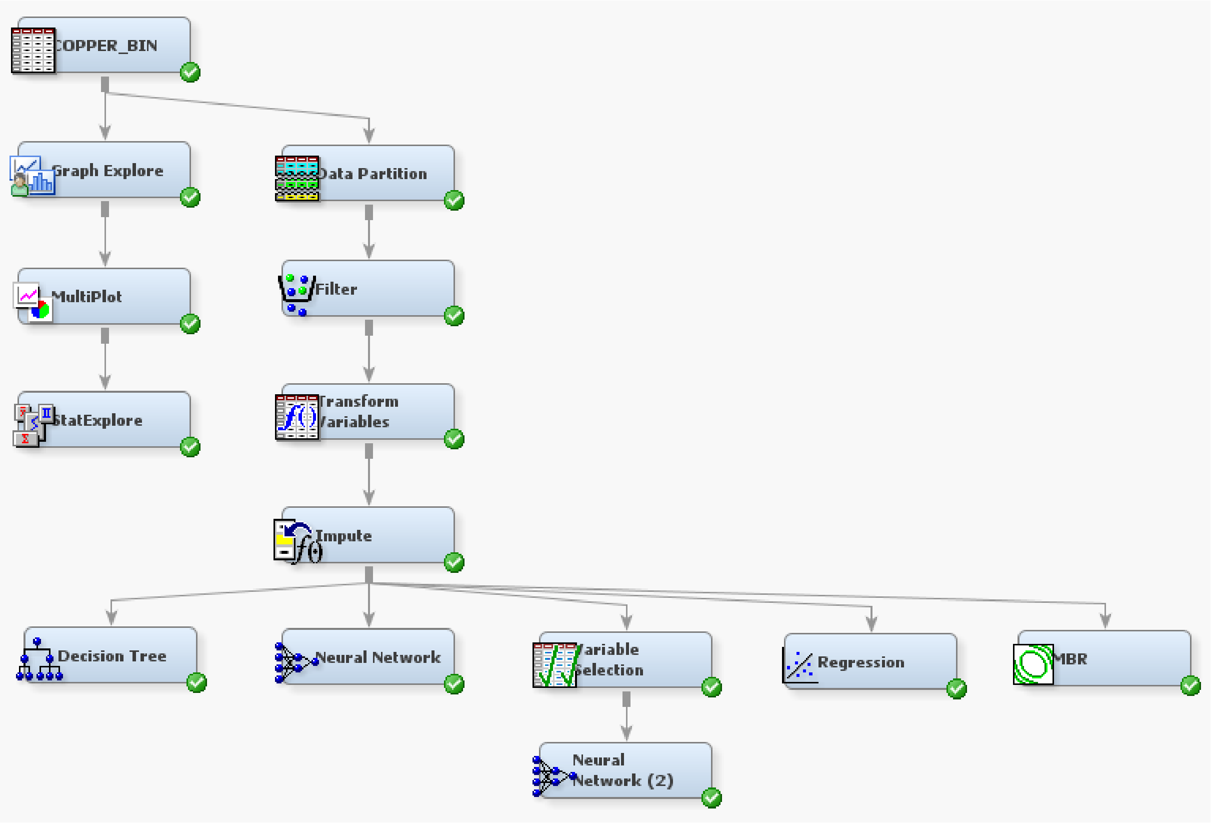
It is generally not clear whether oversampling leads to any significant improvement as compared to the method based on decision weights, considering the fact that oversampling actually *removes* data from the over-represented class (as shown later). Simulation studies indicate that for 3 or more class recognition problems oversampling seems to be the method of choice, however for binary classification little improvement is often observed after rare class recognition has already been boosted by decision weights. The oversampling approach is explained in detail in section Working with imbalanced data – .

Using predictive modelling nodes

We will build and compare five classifiers:

- Decision tree,
- Neural network (multilayer perceptron),
- Neural network preceded by a variable selection node,
- Logistic regression using forward feature selection method,
- Memory Based Reasoning (MBR), which is a simple nonparametric nearest neighbours classifier.

To build these classifiers, predictive modelling nodes should be added to the diagram as shown below.



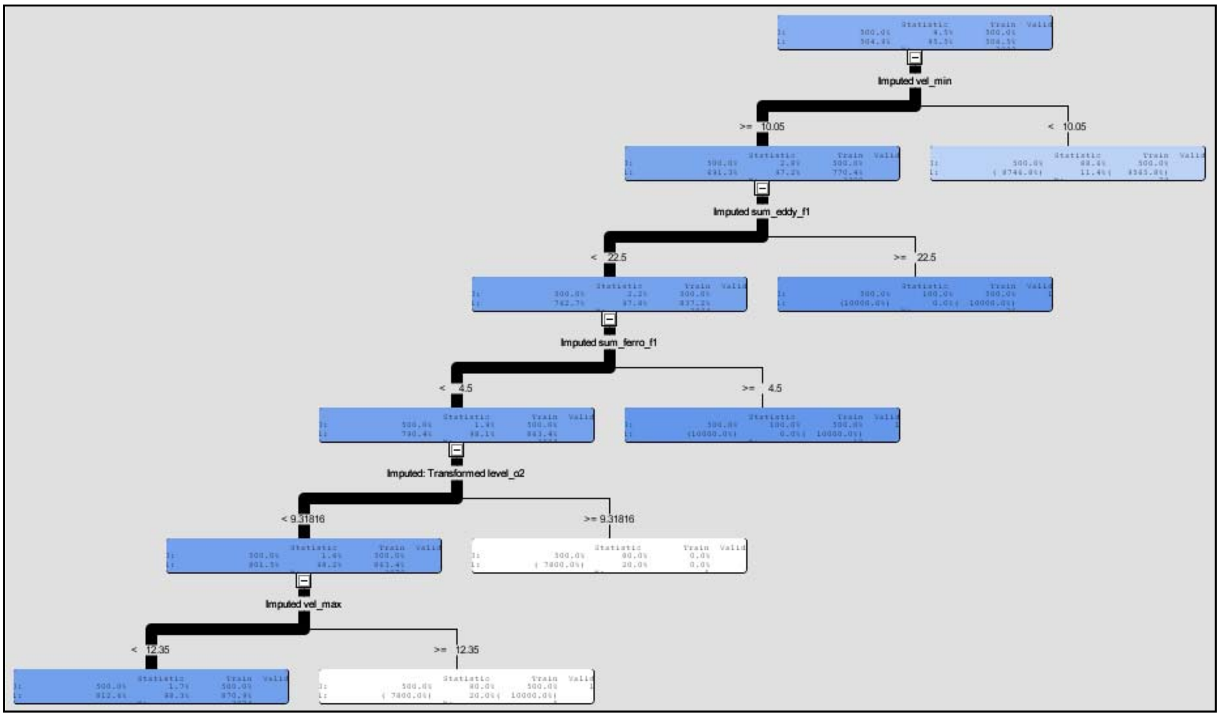
Once the classifiers are fitted to data, the modelling nodes provide the following technical details to the user:

- detailed information about performance of the models measured for the training, validation and test partitions in terms of misclassification rate, total profit etc.,
- detailed information about the fitting process (such as details on subsequent iterations of the forward feature selection process in logistic regression, error rates for subsequent iterations of a neural network, etc.),
- access to the model code in the form of a standalone SAS 4GL program.

Systematic analysis and comparison of performance of the fitted models follows in the section devoted to the Assessment step.

Based on the decision tree model, we will now explain how a model can be analyzed using its Results screen.

The fitted tree is presented graphically, as schematically shown below. Based on performance on validation data, the algorithm fine-tuned the tree to have the depth of 5.

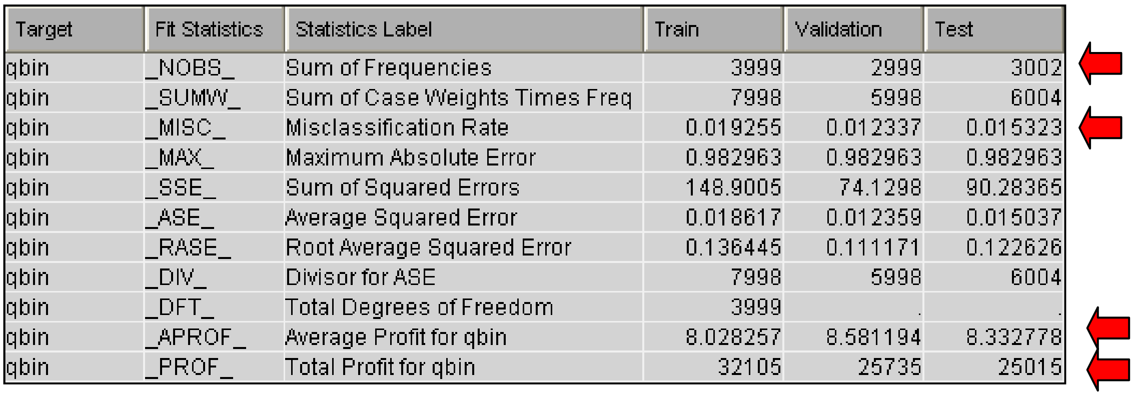


We can examine the tree in the equivalent form of English language rules, where subsequent nodes correspond to the leaf nodes in the graphical representation of the tree. The nodes are related to classification decisions of the tree model, with the majority class in a particular node indicating the tree's answer.

```
IF  Imputed vel_min < 10.050000191
THEN
  NODE    :       2
  N       :      79
  1       :   11.4%
  0       :   88.6%

IF          22.5 <= Imputed sum_eddy_f1
AND 10.050000191 <= Imputed vel_min
THEN
  NODE    :       7
  N       :      26
  1       :    0.0%
  0       :  100.0%

IF           4.5 <= Imputed sum_ferro_f1
AND Imputed sum_eddy_f1 <          22.5
AND 10.050000191 <= Imputed vel_min
THEN
  NODE    :      11
  N       :      10
  1       :    0.0%
  0       :  100.0%

IF  9.3181616203 <= Imputed: Transformed
level_o2
AND Imputed sum_ferro_f1 <          4.5
AND Imputed sum_eddy_f1 <          22.5
AND 10.050000191 <= Imputed vel_min
THEN
  NODE    :      13
  N       :       5
  1       :   20.0%
  0       :   80.0%
```

```
IF  Imputed vel_max < 12.349999905
AND Imputed: Transformed level_o2 <
9.3181616203
AND Imputed sum_ferro_f1 <          4.5
AND Imputed sum_eddy_f1 <          22.5
AND 10.050000191 <= Imputed vel_min
THEN
  NODE    :      14
  N       :    3874
  1       :   98.3%
  0       :    1.7%

IF  12.349999905 <= Imputed vel_max
AND Imputed: Transformed level_o2 <
9.3181616203
AND Imputed sum_ferro_f1 <          4.5
AND Imputed sum_eddy_f1 <          22.5
AND 10.050000191 <= Imputed vel_min
THEN
  NODE    :      15
  N       :       5
  1       :   20.0%
  0       :   80.0%
```

Analyzing the tree model, we can also observe various fit statistics calculated for the training, validate and test partitions:

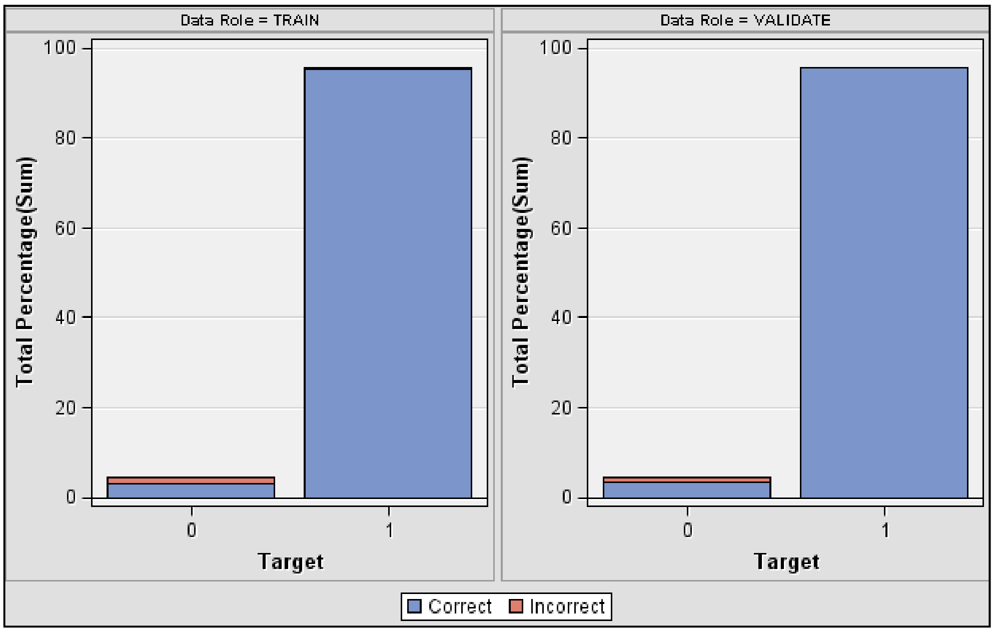


Target	Fit Statistics	Statistics Label	Train	Validation	Test
qbin	_NOBS_	Sum of Frequencies	3999	2999	3002
qbin	_SUMW_	Sum of Case Weights Times Freq	7998	5998	6004
qbin	_MISC_	Misclassification Rate	0.019255	0.012337	0.015323
qbin	_MAX_	Maximum Absolute Error	0.982963	0.982963	0.982963
qbin	_SSE_	Sum of Squared Errors	148.9005	74.1298	90.28365
qbin	_ASE_	Average Squared Error	0.018617	0.012359	0.015037
qbin	_RASE_	Root Average Squared Error	0.136445	0.111171	0.122626
qbin	_DIV_	Divisor for ASE	7998	5998	6004
qbin	_DFT_	Total Degrees of Freedom	3999	.	.
qbin	_APROF_	Average Profit for qbin	8.028257	8.581194	8.332778
qbin	_PROF_	Total Profit for qbin	32105	25735	25015

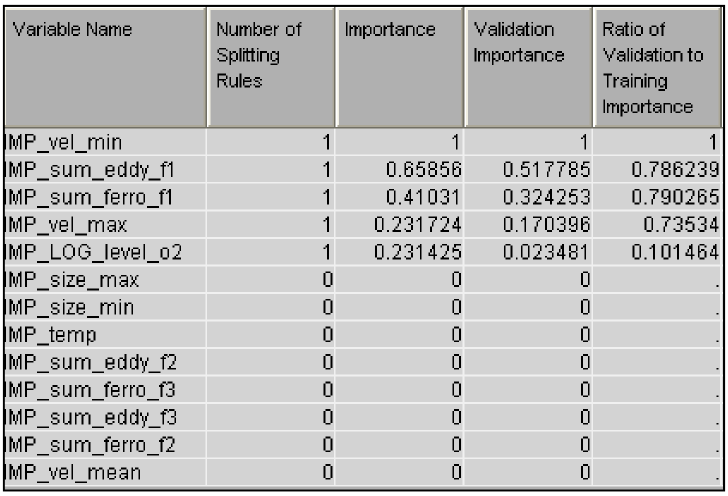
We observe that the misclassification rate for the test data (i.e., expected error rate for new data) equals about 1.5%, and the total profit expected from 3002 items in the test partition equals 25015, which translates into average profit per item of 8.33. Note that if all the items were actually good quality and all classification decisions were correct, then the total profit would amount to about 30 thousand. The difference (of ca 5 thousand) is due to

- some poor quality items in the batch (this accounts for ca 0.75K difference),
- the classifier’s errors (these account for majority of the difference, i.e., over 4K).

Another interesting perspective in analysis of the tree model is based on the Classification chart, where we observe that the rare class (qbin=0) is indeed much more difficult to properly classify, while items of the frequent class are classified almost perfectly.



Analysis of the tree model also provides information about importance of inputs for prediction of target, as shown below. This information may be useful for implementation of feature selection rules. It can be observed that the tree selects only the first five variables on top of the list below as predictors for estimation of the target.



Variable Name	Number of Splitting Rules	Importance	Validation Importance	Ratio of Validation to Training Importance
IMP_vel_min	1	1	1	1
IMP_sum_eddy_f1	1	0.65856	0.517785	0.786239
IMP_sum_ferro_f1	1	0.41031	0.324253	0.790265
IMP_vel_max	1	0.231724	0.170396	0.73534
IMP_LOG_level_o2	1	0.231425	0.023481	0.101464
IMP_size_max	0	0	0	.
IMP_size_min	0	0	0	.
IMP_temp	0	0	0	.
IMP_sum_eddy_f2	0	0	0	.
IMP_sum_ferro_f3	0	0	0	.
IMP_sum_eddy_f3	0	0	0	.
IMP_sum_ferro_f2	0	0	0	.
IMP_vel_mean	0	0	0	.

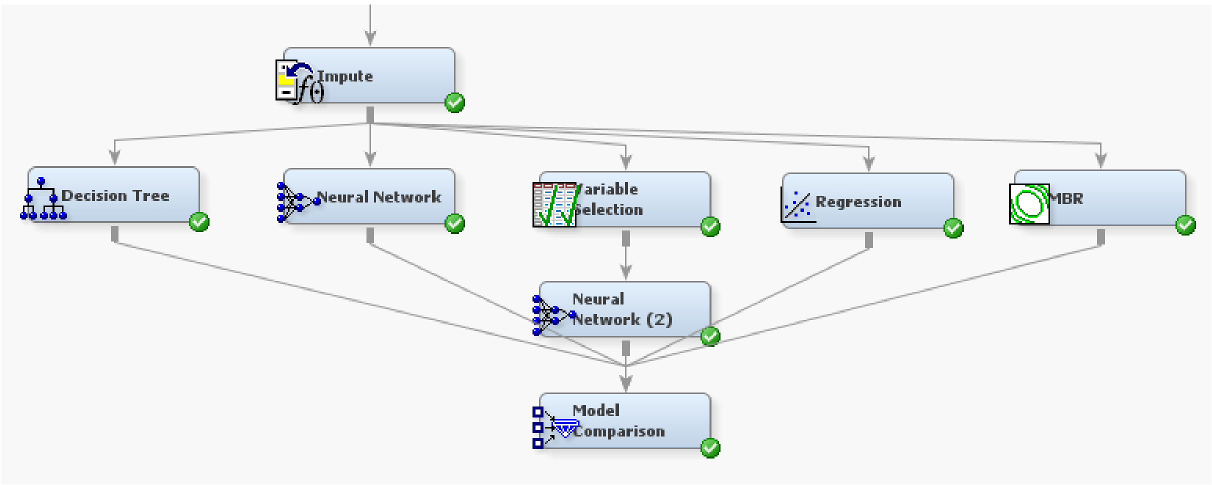
The tree node offers several other interesting methods for analysis of the model, such as e.g., lift analysis. These methods are however more appropriate for problems where the task consists in selection of items with the highest probability of event. In our case, the problem consists in quality prediction of *all* the items with the criterion to minimize the cost of wrong decisions (or maximize overall profit).

Similar in-depth analysis of the fitted models is available with other nodes (Neural Network, Regression, MBR). However, in the next section we will concentrate on comparison of the models in terms of some simple practical criteria.

Assessment of performance of the models

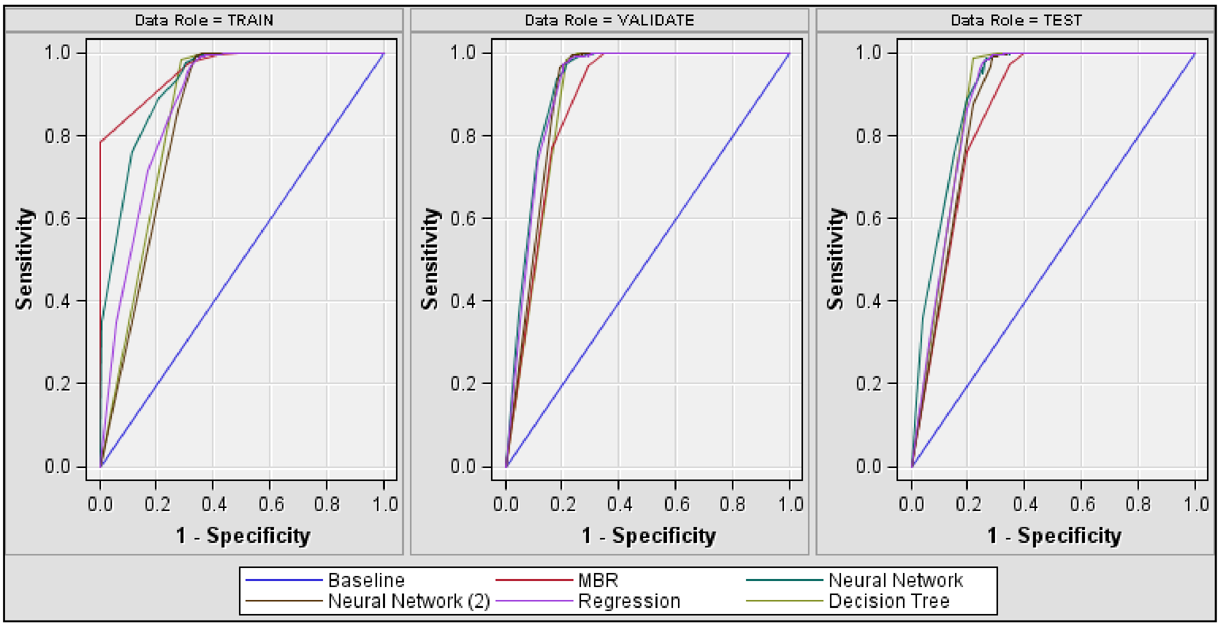
The purpose of this SEMMA step is to evaluate and compare models in terms of their practical usefulness. The models can be compared using several criteria such as the profit/loss, misclassification rate, or using ROC curves or cut-off analysis.

Overall assessment of fitted models is realized with the Model Comparison node, added to the diagram after the modelling nodes (see diagram below).



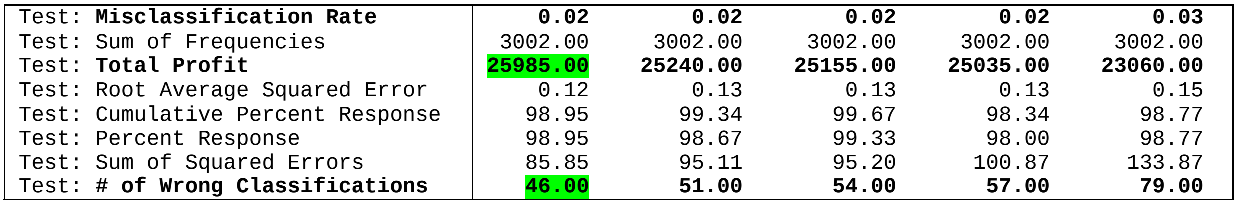
The Model Comparison node provides several tools for analysis of the models, such as the ROC curves as shown below. The ROC analysis indicates that the models demonstrate similar performance, where sensitivity of ca 100% inevitably translates into about 20% (=1-specificity) error rate in recognition of the other (poor quality) class. Note that sensitivity is related to the target event of 1, i.e., recognition of good quality (frequent) class. The ROC analysis is consistent with the rare class recognition problem, described previously.

In terms of selection of the winning model, no firm conclusion can be made based on the ROC curves. The tree, neural network models and regression perform similarly (with slightly better results of the tree expected for the test data), while the MBR (nearest neighbours) classifier is remarkably weaker.



The qualitative conclusions from the ROC analysis can be quantitatively confirmed through a number of criteria summarized in the table below. These measures are calculated for the test partition, i.e., similar performance can be expected for new data. Whereas all the models misclassify roughly 2% of cases, the tree model slightly outperforms other models in terms of the total (and average per decision) profit, as well as in terms of the total number of wrong classifications.

	Tree	Reg	Neural	Neural2	MBR
Test: KS Statistic	0.76	0.72	0.72	0.70	0.62
Test: **Average Profit**	**8.66**	**8.41**	**8.38**	**8.34**	**7.68**
Test: Average Squared Error	0.01	0.02	0.02	0.02	0.02
Test: Roc Index	0.89	0.89	0.91	0.86	0.86
Test: Average Error Function	0.07	0.08	0.08	0.08	0.26
Test: Bin 2Way KS Prob Cutoff	0.99	0.94	0.94	0.97	0.91
Test: Cum % Captured Response	10.39	10.43	10.46	10.32	10.37
Test: Percent Captured Response	5.18	5.16	5.20	5.13	5.17
Test: Freq of Classified Cases	3002.00	3002.00	3002.00	3002.00	3002.00
Test: Divisor for ASE	6004.00	6004.00	6004.00	6004.00	6004.00
Test: Error Function	423.79	464.20	454.30	483.11	1552.93
Test: Gain	3.61	4.01	4.36	2.97	3.43
Test: Gini Coefficient	0.77	0.78	0.82	0.73	0.71
Test: Bin-Based 2Way KS Statistic	0.76	0.72	0.72	0.69	0.62
Test: KS Probability Cutoff	0.80	0.94	0.89	0.92	0.88
Test: Cumulative Lift	1.04	1.04	1.04	1.03	1.03
Test: Lift	1.04	1.03	1.04	1.03	1.03
Test: Maximum Absolute Error	0.99	0.99	1.00	0.99	1.00



Test: **Misclassification Rate**	**0.02**	**0.02**	**0.02**	**0.02**	**0.03**
Test: Sum of Frequencies	3002.00	3002.00	3002.00	3002.00	3002.00
Test: **Total Profit**	**25985.00**	**25240.00**	**25155.00**	**25035.00**	**23060.00**
Test: Root Average Squared Error	0.12	0.13	0.13	0.13	0.15
Test: Cumulative Percent Response	98.95	99.34	99.67	98.34	98.77
Test: Percent Response	98.95	98.67	99.33	98.00	98.77
Test: Sum of Squared Errors	85.85	95.11	95.20	100.87	133.87
Test: **# of Wrong Classifications**	**46.00**	**51.00**	**54.00**	**57.00**	**79.00**

Again, the Model Comparison node provides several other tools for assessment of models, such as lift analysis; these however do not bring useful interpretation for the problem of quality prediction, and hence are omitted in this guide.

More in-depth analysis of the winning model will be presented in the next section on Scoring new data.

Scoring new data

The purpose of this section is to explain

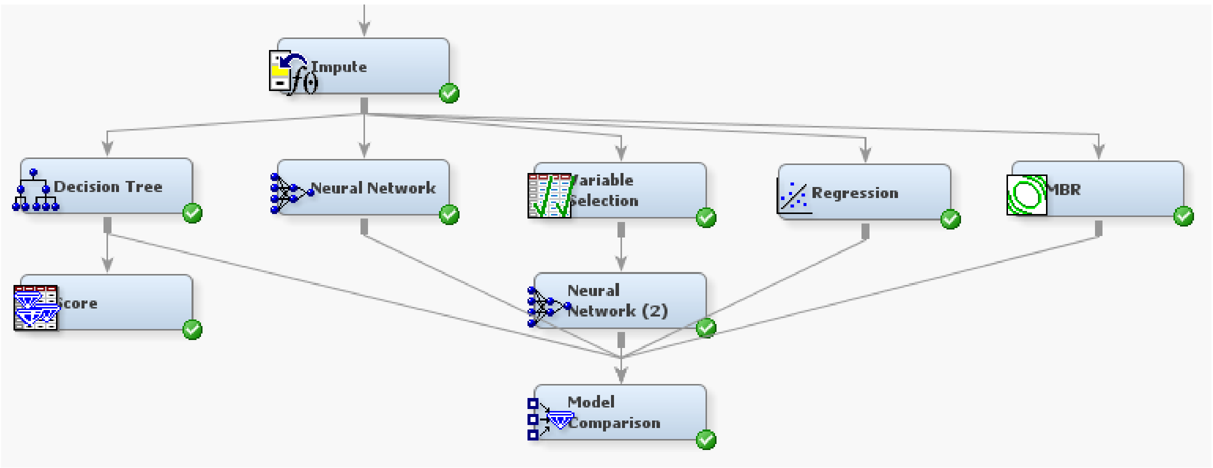
- how the predictive model (e.g., the winning model selected by the Assessment step) can be used to classify (score) new data, and
- how the scoring code can be maintained.

We will also examine contents of the dataset produced by the scoring code and explain how these scored datasets can be the basis for more in-depth analyses using custom SAS coding.

The tool used for scoring new data and for management of scoring codes is the Score node. The node can be connected to:

- any node that produces the scoring code (such as the predictive modelling nodes used in this study),
- the Model Comparison node – in this case the Score node will obtain the winning model from the preceding node (the winning model is selected based on a single criterion specified in the properties of the Model Comparison node).

In this example, we connect the Score node directly to the Decision Tree node, as shown below.

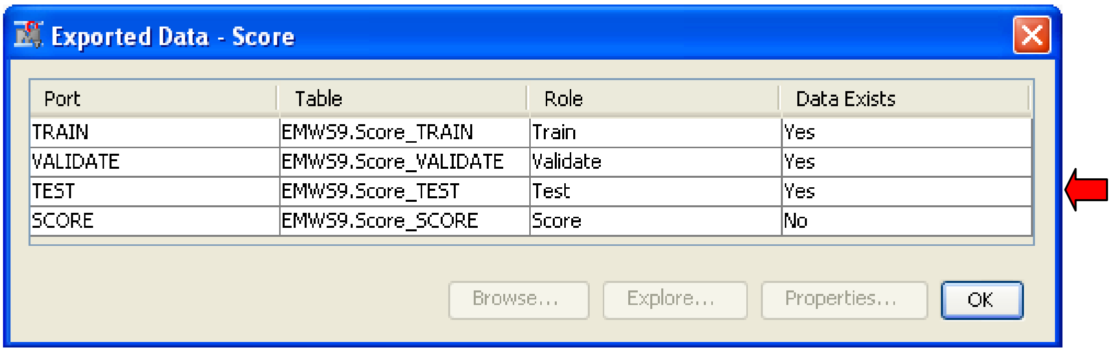


The functionality of the Score node allows to:

- Obtain the scoring code from the preceding node. The scoring code can be then managed outside the Enterprise Miner environment. The scoring code can be exported in the following languages: SAS 4GL, C, Java, PMML.
- Execute the scoring code against a dataset connected to the Score node. Normally, this dataset is connected to the Score node using the Input Data node with the metadata role of Score. Alternatively, the scoring code is applied for the train, validate and test partitions (these data sets are passed through to the Score node).

In this example, we will use the Score node to classify data in the *test* partition, since predictive performance for this partition is a reliable measure of expected performance for new data.

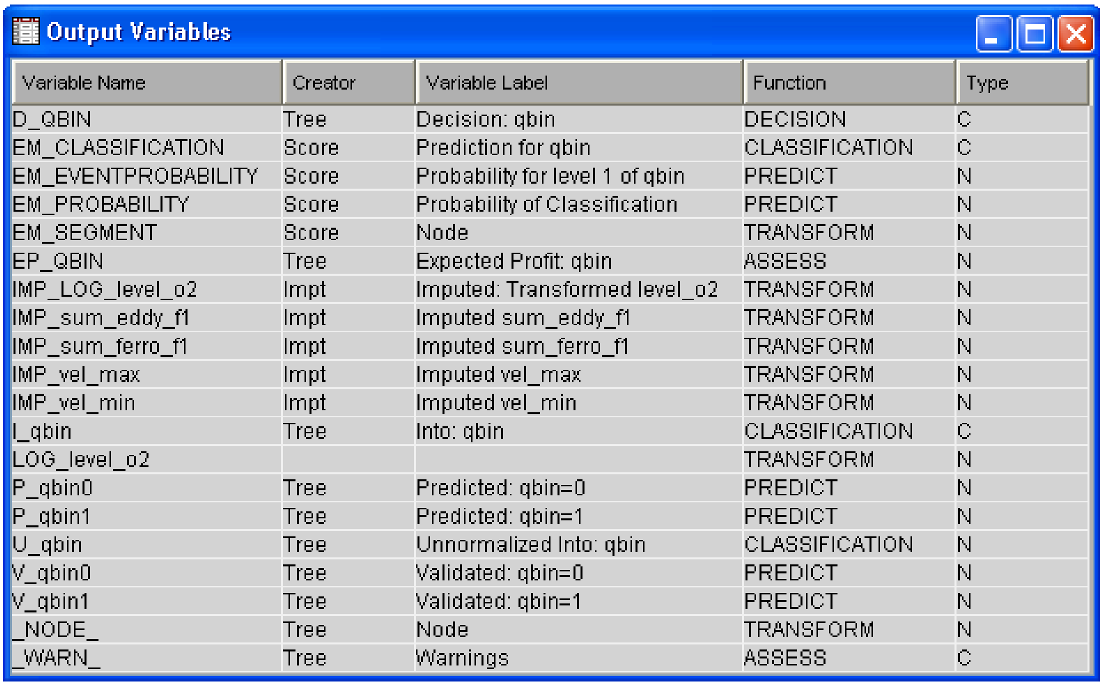
The Exported Data property of the Score node indicates where the results of scoring are placed by the node. In this example the scored test data is found in the EMWS9.Score_TEST dataset.



Exported Data - Score

Port	Table	Role	Data Exists
TRAIN	EMWS9.Score_TRAIN	Train	Yes
VALIDATE	EMWS9.Score_VALIDATE	Validate	Yes
TEST	EMWS9.Score_TEST	Test	Yes
SCORE	EMWS9.Score_SCORE	Score	No

The variables in this dataset involved in the classification process are listed by the node in its Results screen as shown below. These include the predictors used by the tree model as well as variables produced by the tree node or the score node to provide detailed technical information pertaining to the classification process.



Output Variables

Variable Name	Creator	Variable Label	Function	Type
D_QBIN	Tree	Decision: qbin	DECISION	C
EM_CLASSIFICATION	Score	Prediction for qbin	CLASSIFICATION	C
EM_EVENTPROBABILITY	Score	Probability for level 1 of qbin	PREDICT	N
EM_PROBABILITY	Score	Probability of Classification	PREDICT	N
EM_SEGMENT	Score	Node	TRANSFORM	N
EP_QBIN	Tree	Expected Profit: qbin	ASSESS	N
IMP_LOG_level_o2	Impt	Imputed: Transformed level_o2	TRANSFORM	N
IMP_sum_eddy_f1	Impt	Imputed sum_eddy_f1	TRANSFORM	N
IMP_sum_ferro_f1	Impt	Imputed sum_ferro_f1	TRANSFORM	N
IMP_vel_max	Impt	Imputed vel_max	TRANSFORM	N
IMP_vel_min	Impt	Imputed vel_min	TRANSFORM	N
I_qbin	Tree	Into: qbin	CLASSIFICATION	C
LOG_level_o2			TRANSFORM	N
P_qbin0	Tree	Predicted: qbin=0	PREDICT	N
P_qbin1	Tree	Predicted: qbin=1	PREDICT	N
U_qbin	Tree	Unnormalized Into: qbin	CLASSIFICATION	N
V_qbin0	Tree	Validated: qbin=0	PREDICT	N
V_qbin1	Tree	Validated: qbin=1	PREDICT	N
NODE	Tree	Node	TRANSFORM	N
WARN	Tree	Warnings	ASSESS	C

The following variables provide interesting technical information about the process of classification:

D_QBIN Contains the predicted class level (quality of an item). The prediction is done by the classifier fine-tuned to maximize profit (i.e., built using the target profile Decision Weights matrix).

I_QBIN Contains the predicted class label, produced by the classifier fine-tuned to minimize the overall number of misclassified items (i.e., built without using the target profile Decision Weights matrix). The name given to this variable by the scoring node is EM_CLASSIFICATION.

EM_EVENTPROBABILITY The probability associated with the classifier's decision that an item is good quality.

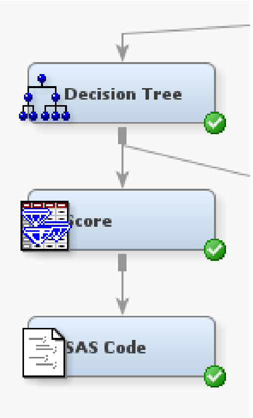
EM_PROBABILITY The probability of the decision finally made by the classifier. This probability is estimated as:

EM_PROBABILITY = max(EM_EVENTPROBABILITY, 1- EM_EVENTPROBABILITY)

Given this technical output appended to the results of scoring dataset (i.e., EMWS9.Score_TEST), further in-depth analysis of the model itself or of the scored data is possible using custom SAS coding.

To illustrate this, we will post-process results of scoring to calculate the *coincidence matrix* and the *sensitivity* and *specificity* parameters of the model.

To do this, the SAS Code node is connected to the Score node, as shown below.



In order to compute the coincidence matrix, the following SAS code is placed in the SAS Code node (the Code Editor is available through properties of this node):

```
proc freq data=emws9.score_test;
  tables qbin*d_qbin;
  tables qbin*i_qbin;
run;
```

PROC FREQ is the SAS/STAT procedure used to produce frequency or contingency tables to examine relationship between two classification variables.

In this example, we use the FREQ procedure to compare:

- the actual quality of copper (qbin) with the quality predicted using the profit maximization rule (this decision is coded in the d_qbin classifier's output variable), or
- the actual quality of copper (qbin) with the quality predicted using the misclassification rate minimization rule (this decision is coded in the i_qbin classifier's output variable).

The coincidence matrixes summarizing performance of these two classifiers are given below. We also calculate the total profit and misclassification rates.

The conclusions can be summarized as follows:

- The model based on decision weights indeed realizes higher total profit as compared to the original classifier (25985 vs. 25015), although the total number of misclassifications is higher (72 vs. 46).
- Improvement in the total profit is achieved by reducing the number of the costly 0→1 classification errors (from 41 to 30), at the expense of increased 1→0 error rate.

```
Classifier fine tuned to maximize the
total profit

Table of qbin by D_QBIN

qbin      D_QBIN(Decision: qbin)

Frequency|
Percent  |
Row Pct  |
Col Pct  |0       |1       |  Total
---------+--------+--------+
       0 |    105 |     30 |    135
         |   3.50 |   1.00 |   4.50
         |  77.78 |  22.22 |
         |  71.43 |   1.05 |
---------+--------+--------+
       1 |     42 |   2825 |   2867
         |   1.40 |  94.10 |  95.50
         |   1.46 |  98.54 |
         |  28.57 |  98.95 |
---------+--------+--------+
Total         147     2855     3002
             4.90    95.10   100.00

TOTAL PROFIT 25985

TOTAL # OF MISCLASSIFICATIONS 72
```

```
Classifier fine tuned to minimize the
misclassification rate

Table of qbin by I_qbin

qbin      I_qbin(Into: qbin)

Frequency|
Percent  |
Row Pct  |
Col Pct  |0       |1       |  Total
---------+--------+--------+
       0 |     94 |     41 |    135
         |   3.13 |   1.37 |   4.50
         |  69.63 |  30.37 |
         |  94.95 |   1.41 |
---------+--------+--------+
       1 |      5 |   2862 |   2867
         |   0.17 |  95.34 |  95.50
         |   0.17 |  99.83 |
         |   5.05 |  98.59 |
---------+--------+--------+
Total          99     2903     3002
             3.30    96.70   100.00

TOTAL PROFIT 25015

TOTAL # OF MISCLASSIFICATIONS 46
```

These models can also be compared in terms of sensitivity and specificity. These parameters compare as follows:

- model on the left: sensitivity=98.54% , specificity=77.78%
- model on the right: sensitivity=99.83% , specificity=69.63%

Observe that (1-specificity) is the misclassification rate for the rare class (poor quality items): this parameter was reduced from ca 30% to 22%. This analysis confirms that the decision weights matrix leads to improvement in recognition of the rare class.

Working with imbalanced data – oversampling technique

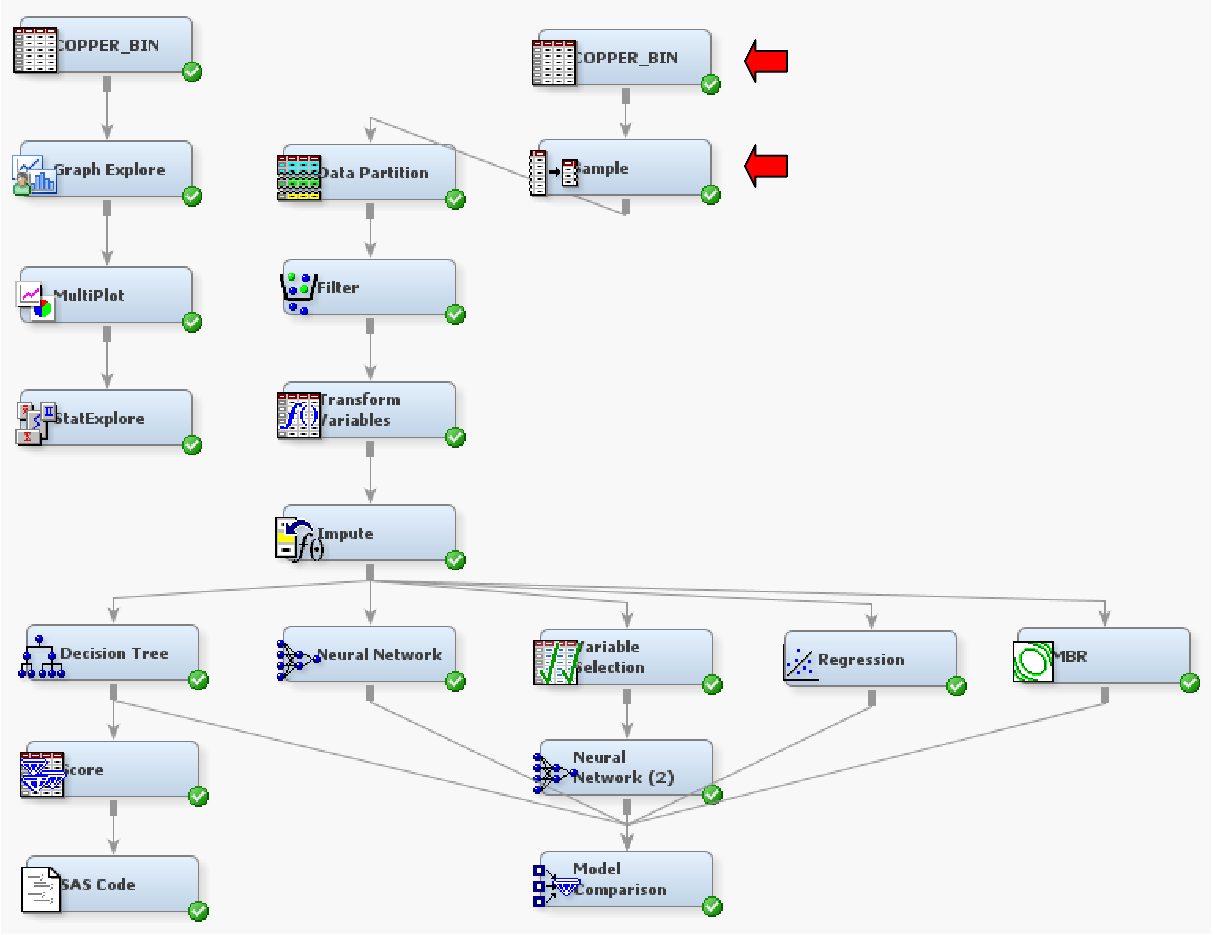
Classifiers built using heavily imbalanced training data (i.e., data where some class shows much lower frequency than other classes) tend to realize low predictive performance of the rare class. We discussed reasons for this previously (see section Working with imbalanced data) and outlined the methods feasible in Enterprise Miner to improve recognition of the rare class.

In the previous section, we demonstrated that a properly designed decision weights matrix can be regarded as a tool to improve recognition of the rare class.

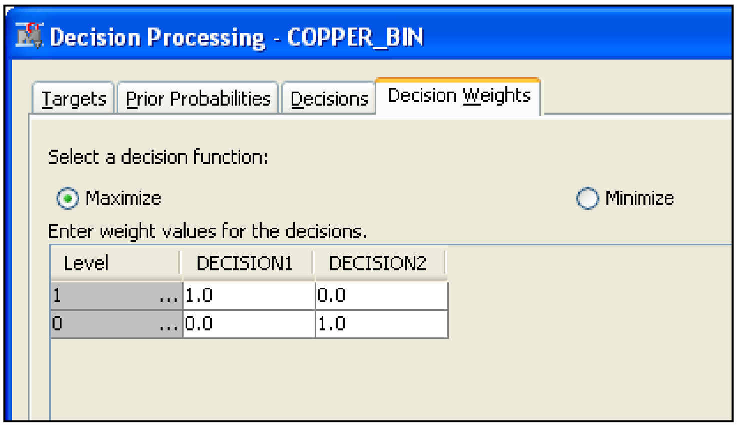
This section is devoted to *data oversampling* – technique commonly discussed in data mining literature. The method consists in preparing a sample of data in which frequencies of classes are more similar to each other than in the original dataset (or even equal), and building a classifier based on this sample. Doing so, we need to make sure that the classifier does not learn false *a priori* (or prior) probabilities of classes, representative for the oversampled data, but completely wrong for the real data.

Here we explain how this task can be implemented in Enterprise Miner and demonstrate performance of this approach. In this example, we focus only on oversampling as a method to improve recognition of the rare class, so the decision weight matrix will not be used, to avoid combining effects of these two approaches. Hence, we modify the process diagram as shown below by adding:

- a new Input Data node (note that we will modify the target profile of this node to remove the effect of non-symmetric decision weights),
- a Sample node (this node needs to be configured to do the actual oversampling).



In configuration of the new Input Data node (which should point to the same data source as the one used before), we make sure that the Decision Weights matrix does not favour any decision (i.e., the costs are symmetric as shown below).



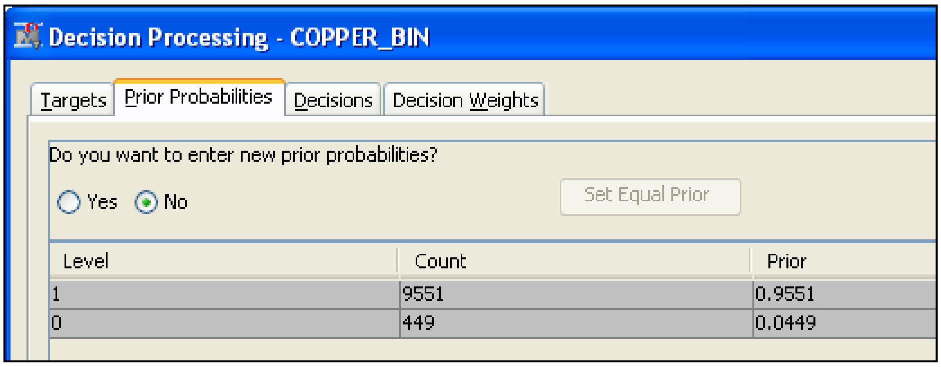
Select a decision function:

● Maximize ○ Minimize

Enter weight values for the decisions.

Level	DECISION1	DECISION2
1 ...	1.0	0.0
0 ...	0.0	1.0

Next, we must make sure that the Prior Probabilities associated with the classes reflect the true frequencies of classes observed in real data. If these values are not set correctly (e.g., due to previously done oversampling of the COPPER_BIN data source), then the classifier will learn improper priors based on frequencies in the oversampled data. In this example, we leave these probabilities as is, as they agree with actual frequencies of good and poor quality items manufactured.

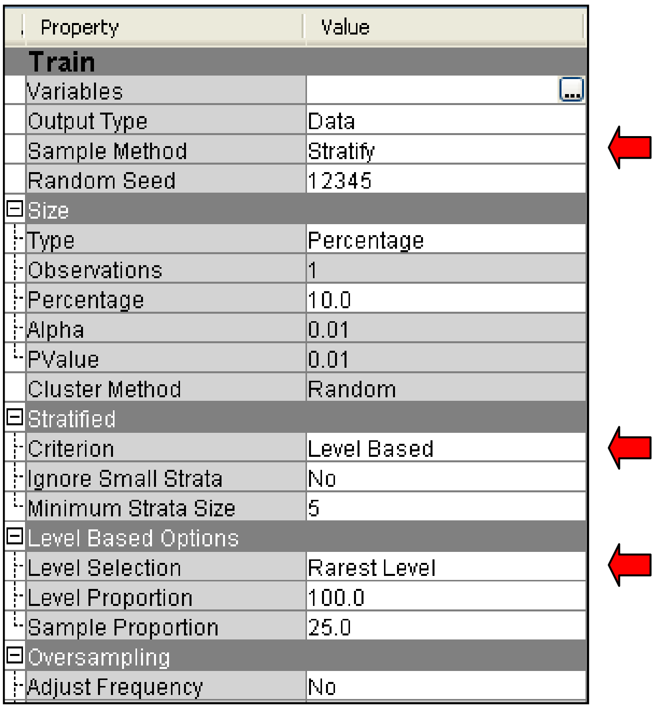


Do you want to enter new prior probabilities?

○ Yes ● No

Level	Count	Prior
1	9551	0.9551
0	449	0.0449

Next, we configure the Sample node for oversampling. The Sample node can be used to realize very diverse scenarios of data sampling. In order to make the node do the oversampling properly, it is essential that the following configuration guidelines are carefully observed.



Property	Value
Train	
Variables	
Output Type	Data
Sample Method	Stratify
Random Seed	12345
⊟ Size	
Type	Percentage
Observations	1
Percentage	10.0
Alpha	0.01
PValue	0.01
Cluster Method	Random
⊟ Stratified	
Criterion	Level Based
Ignore Small Strata	No
Minimum Strata Size	5
⊟ Level Based Options	
Level Selection	Rarest Level
Level Proportion	100.0
Sample Proportion	25.0
⊟ Oversampling	
Adjust Frequency	No

The required configuration elements of the Sample node (as indicated by arrows on the picture above) are explained next.

Sample Method: **Stratify**	This setting guarantees that the algorithm will sample observations from individual classes (or *strata*) so that user specified proportions of the classes are achieved in the sample. These proportions are specified through the Stratified and Level Based Options properties. (If a variable other than the target variable should be used for data stratification, then this variable should be indicated by the Stratification Role in the Variables metadata).
Stratified Criterion: **Level Based**	This setting informs the algorithm that sample proportions will be defined in terms of percentages (or counts) pertaining to the

	fixed level (i.e., value) of the stratification variable. In our case, the sample will be defined based on the level qbin=0 (i.e., the rare class).
Level Based Option Level Selection: **Rarest Level**	This setting means that the sample proportions specified further are related to the rare class (i.e., qbin=0).
Level Based Option Level Proportion: **100**	This setting makes the algorithm create the sample with 100% of the rare class items available in the original dataset (note that this level, i.e., qbin=0 was chosen previously).
Level Based Option Sample Proportion: **25**	This setting means that the selected level (i.e., qbin=0) will contribute 25% observations to the sample, with the remaining 75% randomly selected from the frequent class (qbin=1).

The effect of oversampling can be verified through the Results window of the Sample node (shown below).

```
Data=DATA

            Numeric    Formatted    Frequency
Variable     Value       Value        Count      Percent

  qbin         0           0            449        4.49
  qbin         1           1           9551       95.51


Data=SAMPLE

            Numeric    Formatted    Frequency
Variable     Value       Value        Count      Percent

  qbin         0           0            449       25
  qbin         1           1           1347       75
```

It can be observed that the sample indeed contains all (449) poor quality items available in data. However, in the sample this represents 25% observations, which gives the proportion of the classes in the sample as 1:3. Thus the proportion is significantly higher as compared to the original proportion of ca 1:20 (1:19).

Note however that this scenario actually realizes oversampling of the rare class by "undersampling" of the frequent class. This means that trying to e.g., *balance* proportions of classes would result in a yet smaller sample of 2x449 items. So the obvious problem with oversampling is related to losing (presumably large) part of the training data in the frequent class. It is not clear when this effect of loosing information through oversampling dominates the desired effect of improvement in rare class recognition.

(Note that an alternative oversampling scenario could be implemented, where the rare class observations are actually sampled repeatedly. This is however not implemented in Enterprise Miner and would required custom SAS coding).

In order to observe the effect of oversampling on recognition of the rare class, we execute the SAS Code node (see diagram above). This calculates the coincidence matrix for the tree algorithm, as shown below (construction of the coincidence matrix is explained in section Scoring new data).

This result confirms that recognition of rare class improves due to oversampling. However, based on this results (calculated for oversampled test partition), estimation of the total average profit is not straightforward, as in reality a different proportion of good/poor quality items is expected.

```
Classifier built on oversampled data

Table of qbin by I_qbin

qbin      I_qbin(Into: qbin)

Frequency|
Percent  |
Row Pct  |
Col Pct  |0       |1       |  Total
---------+--------+--------+
       0 |    107 |     28 |    135
         |  19.85 |   5.19 |  25.05
         |  79.26 |  20.74 |
         |  93.04 |   6.60 |
---------+--------+--------+
       1 |      8 |    396 |    404
         |   1.48 |  73.47 |  74.95
         |   1.98 |  98.02 |
         |   6.96 |  93.40 |
---------+--------+--------+
Total         115      424      539
            21.34    78.66   100.00
```

We also observe that improvement in specificity of the classifier obtained here is slightly better than improvement achieved with the decision weights matrix (see previous section). However, we should be cautious trying to interpret this observation as a firm conclusion about higher technical merit of oversampling. We generally observe that oversampling seems to produce lower total profit measure than the decision based approach (results not shown here).

Overall performance of the fitted models is additionally reported by the Model Comparison node through the Event Classification Table (calculated for the train and validation partitions). Below we compare the oversampled model with the original model (no decision weights used). Based on these results, specificity of models (i.e., recognition of rare cases) can be estimated as

$$specificify = \frac{TN}{(TN + FP)}$$

where TN is the number of True Negatives and FP is the number of False Positives summed up for train and validate partitions. We generally observe higher specificity for oversampled models, although at the price of deterioration in models' sensitivity (=TP/(TP+FN)), where TP is the number of True Positives and FN is the number of False Negatives (again summed up for train and validation partitions).

```
MODEL BASED ON OVERSAMPLED DATA

Event Classification Table
Model Selection based on Test: Average Profit (_TAPROF_)

Model                          Data                  False      True       False      True
Node      Model Description    Role       Target   Negative   Negative   Positive   Positive

Tree      Decision Tree        TRAIN       qbin        4         132        47         535
Tree      Decision Tree        VALIDATE    qbin        5          92        43         399
Neural    Neural Network       TRAIN       qbin        9         136        43         530
Neural    Neural Network       VALIDATE    qbin       12          88        47         392
Neural2   Neural Network (2)   TRAIN       qbin        2         128        51         537
Neural2   Neural Network (2)   VALIDATE    qbin        3          88        47         401
Reg       Regression           TRAIN       qbin        6         123        56         533
Reg       Regression           VALIDATE    qbin        6          88        47         398
MBR       MBR                  TRAIN       qbin        2          97        82         537
MBR       MBR                  VALIDATE    qbin        .          62        73         404
```

```
MODEL BASED ON ORIGINAL DATA


Event Classification Table
Model Selection based on Test: Average Profit (_TAPROF_)

Model                          Data                  False      True       False      True
Node      Model Description    Role       Target   Negative   Negative   Positive   Positive

Tree      Decision Tree        TRAIN       qbin       11         114         66        3808
Tree      Decision Tree        VALIDATE    qbin        3         100         34        2862
Neural    Neural Network       TRAIN       qbin        8         105         75        3811
Neural    Neural Network       VALIDATE    qbin        4          91         43        2861
Neural2   Neural Network (2)   TRAIN       qbin        7         110         70        3812
Neural2   Neural Network (2)   VALIDATE    qbin        7          97         37        2858
Reg       Regression           TRAIN       qbin       11          97         83        3808
Reg       Regression           VALIDATE    qbin        7          91         43        2858
MBR       MBR                  TRAIN       qbin        0          72        108        3819
MBR       MBR                  VALIDATE    qbin        0          62         72        2865
```

PART II Data Warehousing

The purpose of this practical guide to data warehousing is to

- learn how online analytical processing (OLAP) methods and tools can be used to perform multidimensional analysis of data,
- get hands-on experience and skills in using MS SQL Server Integration Services (SSIS) and Analysis Services (SSAS) tools for building Extract-Transform-Load (ETL) processes and for building multidimensional data cubes.

The task solved in this example consists in building a multidimensional cube for analysis of student notes at a university (notes from our University were used). The tool will allow to investigate interesting relationships as to how student notes depend on various characteristics of students, teachers, type of course, etc., and how this changes over time. Examples of questions easily answered with the tool built in the lab might be: 'Are older teachers more strict than younger teachers?', or 'Are winter semesters harder than summer semesters?'.

This guide is organised as follows:

- First, an overview of the task is given, including description of the source (input) data, naming the major steps in data processing and outlining the structure of the multidimensional cube to be created.
- Secondly, required ETL and multidimensional data modelling steps are presented in detail.
- Finally, the MS SSIS and SSAS tools to be used for building ETL processes and for multidimensional modelling of data are presented in the tutorial-like fashion.

Overview of this Guide

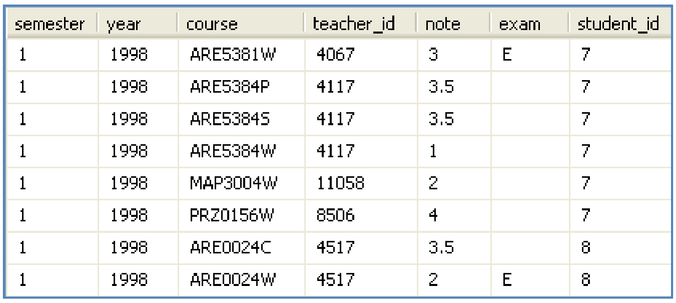
The source data used in the lab contain notes obtained over five subsequent years by a group of students of the Faculty of Electronic Engineering. Some attributes of students, teachers, and courses are also included. The data is provided in the form of five text files: notes.csv, students.csv, teachers.csv, course_group.csv, teacher_title.csv. Samples of these files are shown in Table 2 through Table 6.

The purpose of the class is to build an OLAP solution (a data warehouse and a multidimensional cube) for analysis of student notes. This will be realized by building multidimensional model of the data with the column note used as the fact variable and the remaining columns used as dimensions (dimension attributes).

The task will be realized in following steps:

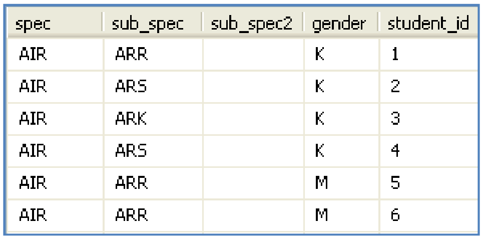
1. Building ETL process,
2. Building multidimensional model of data,
3. Building multidimensional cube.

Table 2 Sample of the notes table



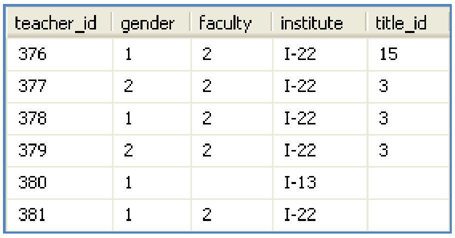
semester	year	course	teacher_id	note	exam	student_id
1	1998	ARE5381W	4067	3	E	7
1	1998	ARE5384P	4117	3.5		7
1	1998	ARE5384S	4117	3.5		7
1	1998	ARE5384W	4117	1		7
1	1998	MAP3004W	11058	2		7
1	1998	PRZ0156W	8506	4		7
1	1998	ARE0024C	4517	3.5		8
1	1998	ARE0024W	4517	2	E	8

Table 3 Sample of the students table



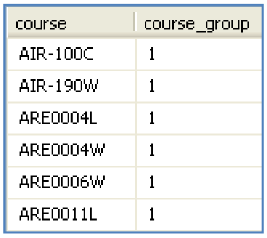
spec	sub_spec	sub_spec2	gender	student_id
AIR	ARR		K	1
AIR	ARS		K	2
AIR	ARK		K	3
AIR	ARS		K	4
AIR	ARR		M	5
AIR	ARR		M	6

Table 4 Sample of the teachers table



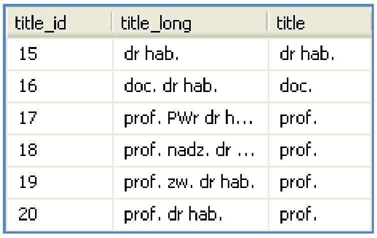
teacher_id	gender	faculty	institute	title_id
376	1	2	I-22	15
377	2	2	I-22	3
378	1	2	I-22	3
379	2	2	I-22	3
380	1		I-13	
381	1	2	I-22	

Table 5 Sample of the course_group table



course	course_group
AIR-100C	1
AIR-190W	1
ARE0004L	1
ARE0004W	1
ARE0006W	1
ARE0011L	1

Table 6 Sample of the teacher_title table



title_id	title_long	title
15	dr hab.	dr hab.
16	doc. dr hab.	doc.
17	prof. PWr dr h...	prof.
18	prof. nadz. dr ...	prof.
19	prof. zw. dr hab.	prof.
20	prof. dr hab.	prof.

Step 1 Building ETL process

Prior to loading data into the data warehouse, errors and/or inconsistencies in the data should be fixed. This is the purpose of Extract-Transform-Load (ETL) scripts. In our source data, several types of inconsistencies can be observed, e.g.,

- Missing or illegal values in some columns (e.g., illegal values of note),
- Inconsistent and/or unclear coding conventions (e.g., student's gender and teacher's gender),
- Problems with foreign key (FK) – primary key (PK) relationships between the fact table and dimension tables (explained in the next section).

Another purpose of the ETL scripts is to modify the structure of the data by deriving new variables and / or new tables to form interesting new dimensions. Examples of these may include the workload table (shown in Figure 4), not available in the source data but calculated in the ETL stage. Generally, restructuring the data at the ETL stage is supposed to simplify multidimensional modelling of data (the task realized as Step 2).

The ETL step will be realized using the tools from MS SQL Server Integration Services (SSIS) available through SQL Server Business Intelligence Development Studio Integration Services project. A sample ETL process used to load, clean and integrate the source data is outlined in Figure 3.

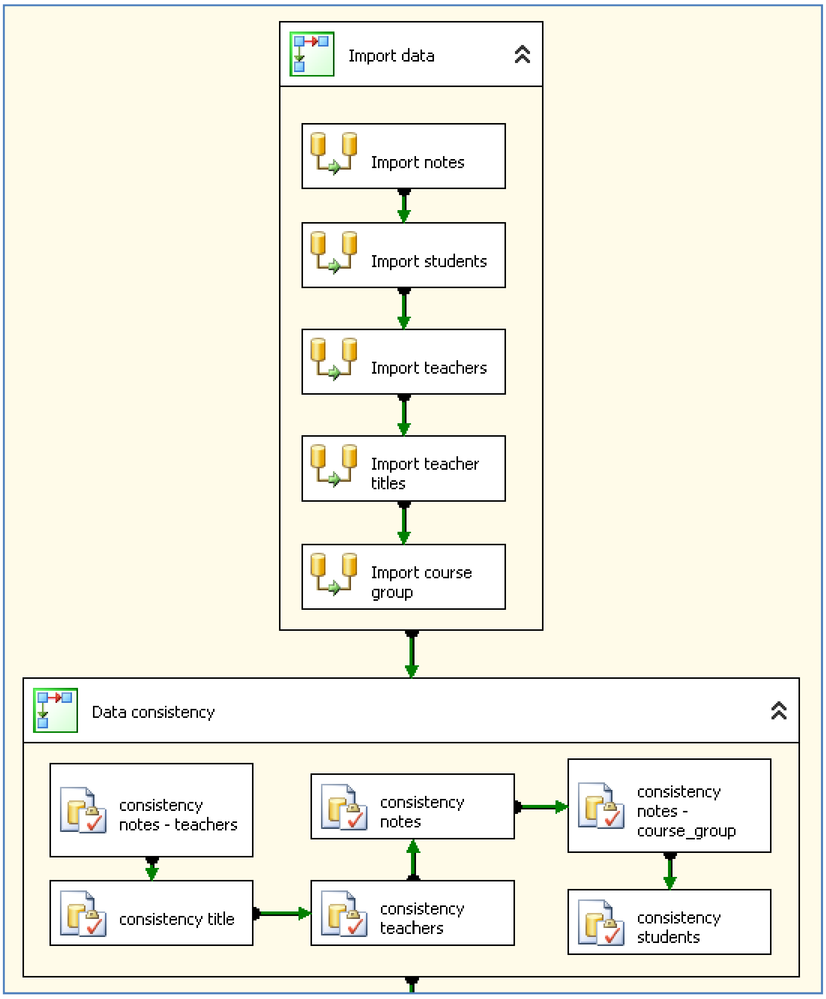


Figure 3 Overview of a sample ETL process in SSIS tool

Step 2 Building multidimensional model of data

This step consists in building the multidimensional model of the data with the fact and dimension tables (see e.g., Figure 4). Since the purpose of the exercise is to analyse notes as a function of attributes of students, teachers etc., the fact table (notes_fact_table) will contain:

- note as the analysis variable,
- foreign keys (FKs) to dimension tables (such as student dimension, teacher dimension, etc.).

For instance, the fact table variables note_desc_id, course, teacher_id and student_id are FK to the dimension tables note_desc (note description), course_group, teachers and students, respectively. The fact table variables teacher_id and semester form the composite FK to the dimension table workload.

It can be also noticed that the structure of multidimensional data (Figure 4) does not directly mimic the layout of the source tables (Table 2 - Table 6), e.g., new tables were introduced (notes_desc and workload) as well as several new variables were derived. These changes, done by ETL restructuring scripts (not shown in Figure 3), greatly simplify multidimensional presentation of data.

The tool used to construct the multidimensional model of data is MS SQL Server Analysis Services available through SQL Server Business Intelligence Development Studio Analysis Services project.

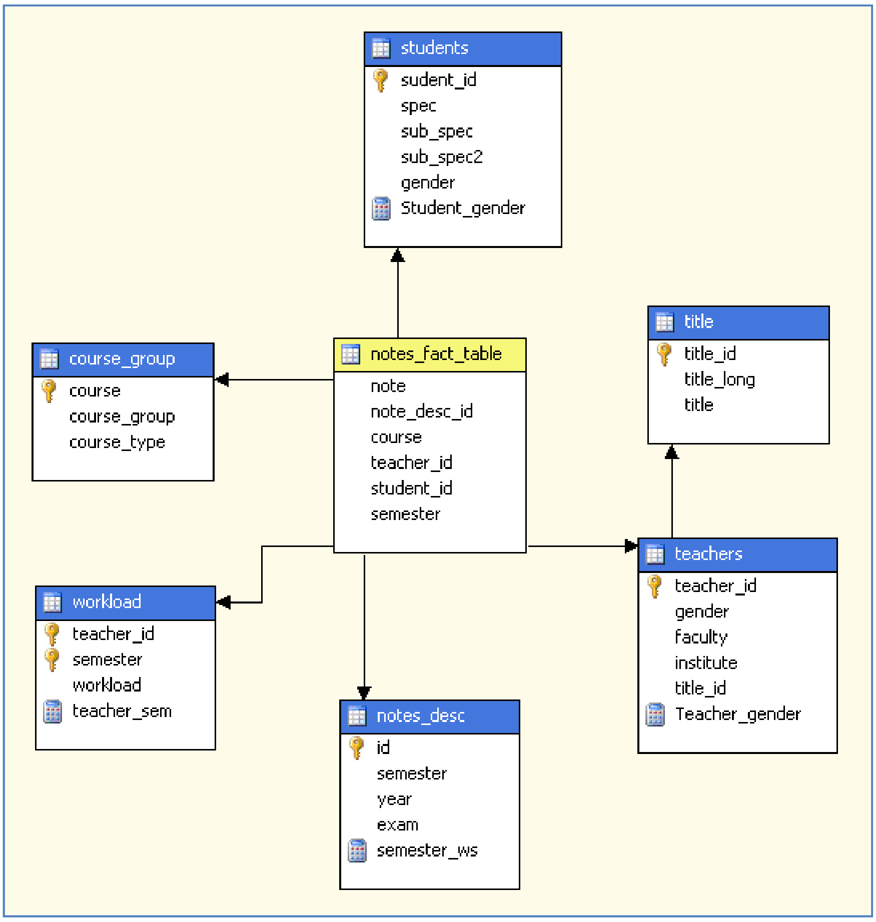


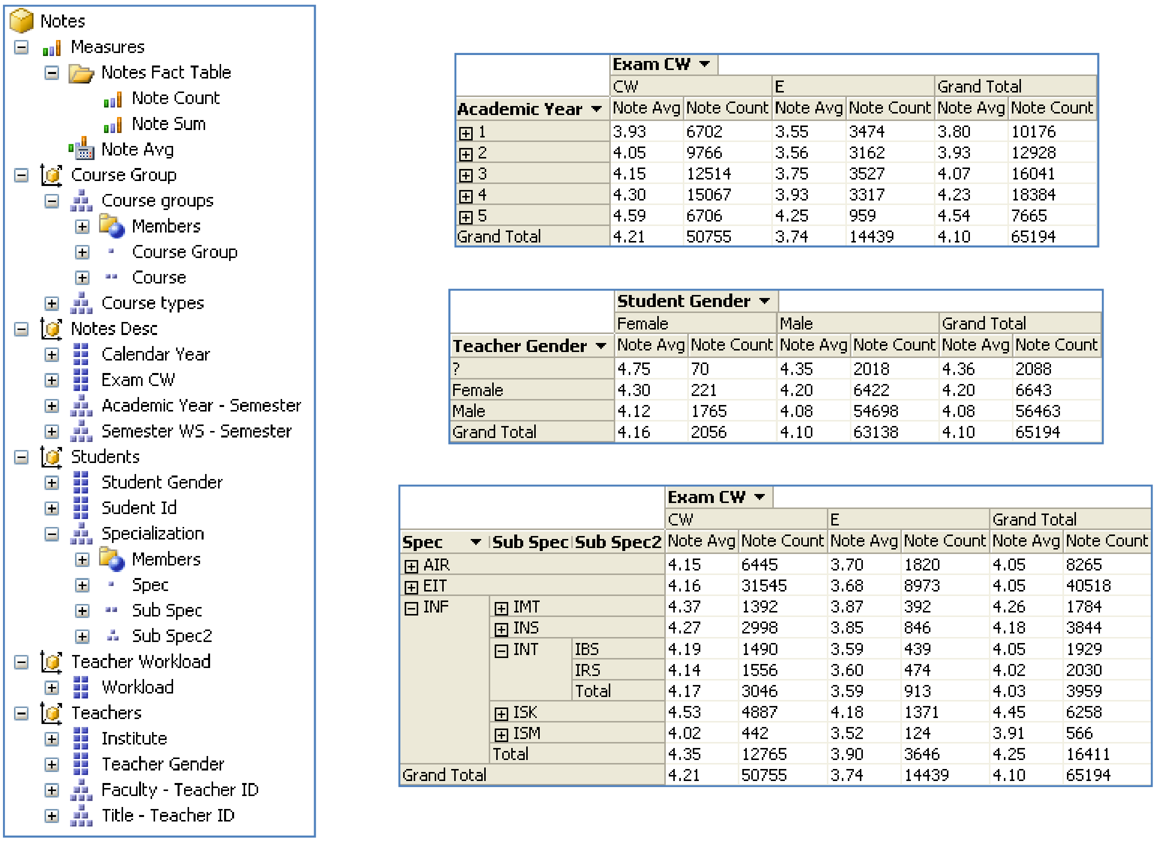
Figure 4 Multidimensional model of data in Analysis Services tool

Step 3 Building multidimensional cube

Based on the multidimensional model of data, the multidimensional cube will be designed. This involves defining proper measures (i.e., statistics of the analysis variable note) to be included in the cube as well as designing cube dimensions. An example of this is shown in the left panel of Figure 5. This cube includes three measures (Note count, Note sum, Note avg), as well as five dimensions (Course Group, Notes Desc, Students, Teacher Workload, Teachers). Some of the dimension attributes are grouped in hierarchies to simplify drill-down analysis, e.g., Semester WS – Semester hierarchy (element of the Notes Desc dimension).

The last step will be to build and deploy the cube into Analysis Services server (server of multidimensional data). Once deployed, the cube can be queried using a multidimensional data browser or using MDX querying language. Sample analyses obtained from the cube are shown in the right panel of Figure 5, where course-work notes (CW) are compared with exam notes (E) in terms of the average note (Note Avg) and the number of notes (Note Count), etc.

The tool used to design structure of the multidimensional cube and to build and deploy the cube is Analysis Services (available in SQL Server Business Intelligence Development Studio Analysis Services project).



- Notes
  - ⊟ Measures
    - ⊟ Notes Fact Table
      - Note Count
      - Note Sum
    - Note Avg
  - ⊟ Course Group
    - ⊟ Course groups
      - ⊞ Members
      - ⊞ Course Group
      - ⊞ Course
    - ⊞ Course types
  - ⊟ Notes Desc
    - ⊞ Calendar Year
    - ⊞ Exam CW
    - ⊞ Academic Year - Semester
    - ⊞ Semester WS - Semester
  - ⊟ Students
    - ⊞ Student Gender
    - ⊞ Sudent Id
    - ⊟ Specialization
      - ⊞ Members
      - ⊞ Spec
      - ⊞ Sub Spec
      - ⊞ Sub Spec2
  - ⊟ Teacher Workload
    - ⊞ Workload
  - ⊟ Teachers
    - ⊞ Institute
    - ⊞ Teacher Gender
    - ⊞ Faculty - Teacher ID
    - ⊞ Title - Teacher ID

	Exam CW ▾					
	CW		E		Grand Total	
Academic Year ▾	Note Avg	Note Count	Note Avg	Note Count	Note Avg	Note Count
⊞ 1	3.93	6702	3.55	3474	3.80	10176
⊞ 2	4.05	9766	3.56	3162	3.93	12928
⊞ 3	4.15	12514	3.75	3527	4.07	16041
⊞ 4	4.30	15067	3.93	3317	4.23	18384
⊞ 5	4.59	6706	4.25	959	4.54	7665
Grand Total	4.21	50755	3.74	14439	4.10	65194

	Student Gender ▾					
	Female		Male		Grand Total	
Teacher Gender ▾	Note Avg	Note Count	Note Avg	Note Count	Note Avg	Note Count
?	4.75	70	4.35	2018	4.36	2088
Female	4.30	221	4.20	6422	4.20	6643
Male	4.12	1765	4.08	54698	4.08	56463
Grand Total	4.16	2056	4.10	63138	4.10	65194

			Exam CW ▾					
			CW		E		Grand Total	
Spec ▾	Sub Spec	Sub Spec2	Note Avg	Note Count	Note Avg	Note Count	Note Avg	Note Count
⊞ AIR			4.15	6445	3.70	1820	4.05	8265
⊞ EIT			4.16	31545	3.68	8973	4.05	40518
⊟ INF	⊞ IMT		4.37	1392	3.87	392	4.26	1784
	⊞ INS		4.27	2998	3.85	846	4.18	3844
	⊟ INT	IBS	4.19	1490	3.59	439	4.05	1929
		IRS	4.14	1556	3.60	474	4.02	2030
		Total	4.17	3046	3.59	913	4.03	3959
	⊞ ISK		4.53	4887	4.18	1371	4.45	6258
	⊞ ISM		4.02	442	3.52	124	3.91	566
	Total		4.35	12765	3.90	3646	4.25	16411
Grand Total			4.21	50755	3.74	14439	4.10	65194

Figure 5 Structure of the multidimensional cube for analysis of notes (left), and sample results of analysis produced from the cube (right)

Tasks in Detail

Task	Description
1	Import source data Using MS VS Integration Services project, load the source files notes.csv, students.csv, teachers.csv, course_group.csv, teacher_title.csv into MS SQL database. Meaning and type of each column is explained below.

Table notes	
semester	Semester number Integer in range 1..10
year	Calendar year Integer in range 1980..
course	Id of course Text, up to 10 characters in length

teacher_id	Id of a teacher who granted a note to a student Integer in range 0..99999
note	A note obtained by a student in a course Real value, legal values: 2, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5
exam	Value ‘E’ identifies a note obtained in an exam, empty value identify notes based on course-work performance of a student.
student_id	Id of a student who received the note Integer in range 0..999999

Table students	
spec	Specialization of the student (AIR – Automatics & Robotics; EIT – Electronics & Telecommunication; INF – Computer Engineering) Text, 3 characters in length
sub_spec	Sub-specialization within specialization groups Text, 3 characters in length
sub_spec2	Some (rare) sub-specializations are further split into groups defined by this value. For most sub-specializations this column is empty. Text, 3 characters in length
gender	Gender of a student ‘K’ – female, ‘M’ – male
student_id	Id of a student, PK of this table Integer in range 0..999999

Table teachers	
teacher_id	Id of a teacher, PK of this table Integer in range 0..99999
gender	Gender of a teacher 1 – male, 2 – female
faculty	Id of the Faculty the teacher is affiliated with (value of 4 denotes Faculty of Electronic Engineering) Integer in range 1..12
institute	Id of the Institute the teacher is affiliated with Text, up to 5 characters in length
title_id	Id of teacher’s title, used to relate to the teacher_title table Integer in range 0..40

Table course_group	
Course	Id of a course, PK of this table Text, up to 10 characters in length
course_group	1 – science and technical courses 2 – sports 3 – foreign languages 4 – social science and management courses

Table teacher_title	
title_id	Id of teacher’s title, PK of this table Integer in range 0..50
title_long	Teacher’s full title Text, up to 30 characters in length
Title	Teacher’s short title Text, up to 10 characters in length

2	Fix data value inconsistencies / unclear coding conventions Some columns contain wrong values (e.g., note = 0 or 1), these values should be removed. Some columns also contain missing values, these should be filled in with some meaningful data (e.g., empty exam column can be filled in with text ‘CW’ (course work)). Empty values interpreted as information not available should be changed into text ‘unknown’ or ‘?’, etc. Gender in teachers and student tables should be coded consistently using symbols clear to end user.
3	Fix consistency of relationships between tables Consistency of foreign key – primary key (PK) relationships between tables should be verified, and, if needed, corrected. For instance, teacher_id in notes table is FK to teachers table. However, source data is not consistent and this relationship is broken as some values of FK (teacher_id) in notes table are missing in teachers table. The way to correct this is to add the missing teacher_id entities to the teachers table. All remaining attributes for these teachers should be coded as unknown (gender, faculty, institute, title). The same procedure should be carried out for FK – PK relationships between other tables (notes – course_group, etc., see Figure 4).
4	Derive new dimension attributes Several interesting attributes are not directly available in source data, e.g., semester type (winter semesters vs summer semesters). Such new columns should be derived, which later allows to add new interesting dimension attributes to the cube. Proposed new attributes: • Semester type (winter/summer semesters based on whether semester number is odd/even) • Academic year of studies (semesters 1,2 – 1st year, semesters 3,4 – 2nd year, etc.) • Course type – based on the last character of the course symbol (W=Lecture, L=lab, P=Project, S=Seminar, C=Exercise).
5	Derive workload table (workload dimension) A new dimension that describes per-semester workload of teachers (and/or workload of students) should be derived. Workload can be defined as the number of notes a teacher grants to the students in a given semester, or, alternatively, as the number of different courses a teacher gives in a semester. The teacher workload table should be created with the columns teacher_id and semester used as the composite PK.
6	Restructure the fact table notes The fact table should include only the fact variable (note) and FKs to dimension tables (as in Figure 4). This can be achieved by moving non-FK columns from the fact table to a separate table (denoted in Figure 4 as notes_desc) and placing the FK to this table in the fact table (denoted in Figure 4 as notes_desc_id).
7	Create a multidimensional cube Using MS VS Analysis Services project, a cube should be designed with the notes fact table

	and dimension tables pertaining to students, teachers, courses, teacher workload, and other notes description (such as those created in task 2).
8	Edit measures in the cube The cube should allow for analysis of the following statistics: the number of notes and the average note. Thus, the measures in the cube should include sum of notes and count of notes. A calculated member average note should be then defined for the cube, based on ratio of these two measures.
9	Edit dimensions Edit all the dimensions (teacher, student, course, notes descriptions and workload dimension) by adding relevant attributes. Proposed structure of dimensions is shown in Figure 5. Related dimension attributes should be grouped into drill-down hierarchies, e.g., Specialization hierarchy (Figure 5), which groups Spec→Sub Spec→Sub Spec2 attributes. Notice: good practice should be observed to hide in the cube structure dimension attributes used as levels of hierarchies.
10	Build and deploy the cube Once designed, the cube should be deployed on the instance Analysis Services. The cube is ready to be browsed with an OLAP viewer or queried using MDX language.
11	Analyze the cube and demonstrate some interesting relationships / trends pertaining to notes at our Faculty.

How-To Procedures and Hints

The purpose of this part is to:

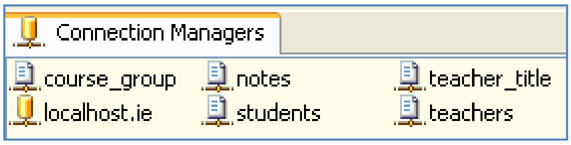
- explain how subsequent tasks can be realized with MS SQL Server Integration Services (SSIS) and Analysis Services (SSAS),
- provide some hints and ideas on how inconsistencies in source data can be corrected.

Hint	Problem and solution
1	How to import source csv files to MS SQL database? 1. In SQL Server Business Intelligence Development Studio create new Integration Services project. 2. Create new Flat File Connection Manager (right click in Connection Manager pane). Edit this Connection Manager to provide location of the source file as well as formatting details (such as column delimiters, etc.). Care should be taken to specify the proper type of each column – compliant with the information detailed in Task 1. 3. Create new OLE DB Connection Manager. This Connection Manager is used to specify name of the database used to store imported tables. 4. Create new Data Flow Task (drag and drop Data Flow icon from toolbox onto the Control

Flow pane).

5. Put Flat File Source into this Data Flow Task and specify the appropriate Flat File Connection Manager.
6. Put OLE DB Destination into this Data Flow Task and connect Flat File Source to this OLE DB Destination. Edit the OLE DB Destination to specify right OLE DB Connection Manager and request New table to store imported data. Notice that this will create the destination DB table, with the generated SQL CREATE TABLE statement shown after pressing the New (table or view) button. It should be verified that the name of the destination table and types of columns are correct (the name of the destination table is taken after the name of the OLE DB Destination tool).
7. To import source csv file into the DB table, run the Data Flow Task (right click on its icon).

Repeat steps 2,4-6 of this procedure for the remaining source files. As a result, five Flat File Source Connection Managers, and one OLE DB Connection Manager will be created, as shown below. The Data Flow Tasks created can be grouped using Sequence Container (as shown in Figure 3).



Connection Managers

course_group
localhost.ie
notes
students
teacher_title
teachers

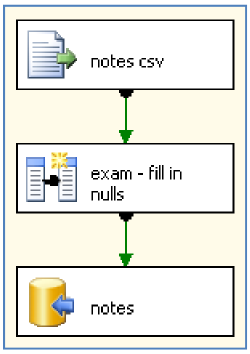
Notice

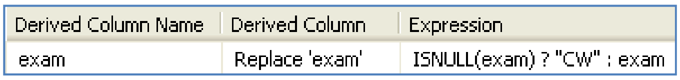
Care should be taken how null values in source tables are loaded using Flat File (FF) Source tool. When the FF Source option "Retain null value" is checked, nulls (coded as ,, in csv files) will be loaded as NULL into the database. This makes it possible to use constructs like `WHERE teacher_is IS NULL` or expressions like `ISNULL(teacher_id)`, etc. (see Hint 2).

2 How to clean imported data / modify wrong values / fill in null values?

Using Data Transformation tools in Data Flow Task

New columns can be derived or existing columns can be conditionally modified using Derived Column in the data transformation flow, as shown below. The expression shown in this example is used to overwrite null values in the exam column with an explicit symbol of course-work notes ("CW", as opposed to exam notes, coded explicitly by "E").





Derived Column Name	Derived Column	Expression
exam	Replace 'exam'	ISNULL(exam) ? "CW" : exam

Rows can be conditionally deleted from a table using Conditional Split transformation.

Using explicit SQL code

Data cleaning transformations can be alternatively written as SQL scripts placed in Execute

SQL Task (elements in Control Flow). All data consistency elements shown in Figure 3 are examples of this approach. For instance, below is a simple script used to recode teacher's gender (SQL Task consistency teachers in Figure 3):

```
UPDATE teachers
SET gender =
  CASE
    WHEN gender = '1' THEN 'M'
    WHEN gender = '2' THEN 'F'
    ELSE '?'
  END
```

3 How to fix foreign key – primary key relationships between tables

The problem will be explained on the example of the dimension teachers (FK – PK relationship between notes fact table and teachers table).

Verification of consistency of FK – PK relationship
It should be checked if any of values of the FK (teacher_id) in the fact table are missing in the dimension table, if so (as in our source data) – the relationship is broken.
The idea of SQL code used for verification of the relationship is given below.

```
SELECT n.teacher_id
FROM notes as n
LEFT JOIN teachers AS t ON n.teacher_id = t.teacher_id
WHERE (t.teacher_id IS NULL)
GROUP BY n.teacher_id
```

Correction of inconsistent relationship
Teacher ids missing from the teachers table should be added to teachers dimension, forming entities with the remaining columns (teacher gender, etc.) filled with values coding 'information not available'.
The idea of an SQL script to correct broken relationships is given below.

```
INSERT INTO teachers
SELECT n.teacher_id, ‘?’ AS gender, etc...
FROM notes as n
LEFT JOIN teachers AS t ON n.teacher_id = t.teacher_id
WHERE (t.teacher_id IS NULL)
GROUP BY n.teacher_id
```

4 How to create dimensions based on non-FK columns of the fact table

Method 1
The idea is to create a new dimension table with non-FK columns of the fact table (such as e.g., semester, etc.; this table is named notes_desc in Figure 4). FK to this table will be placed in the fact table in place of the columns in this new dimension (these columns will be removed from the original notes table).
The first step is to create a temporary (aggregate) notes table with the id used as the PK in the new dimension table and FK in the new fact table. The table will be then split into the notes fact table and the new dimension table.
The idea of the first step is given below.

```
SELECT
  IDENTITY (bigint, 1, 1) AS id,
  all remaining columns of the fact table...
INTO
  notes_tmp
FROM
  notes
```

Then the temporary table should be split into the new dimension table:

```
SELECT
  id , semester, etc.
INTO
  notes_desc
FROM
  notes_tmp
```

and into the fact table (notice that only the fact variable and FKs to dimension tables are being selected):

```
SELECT
  note, id AS note_desc_id, remaining FKs to other dimension tables
INTO
  notes_fact_table
FROM
  notes_tmp
```

The multidimensional model of data formed in this way is shown in Figure 4.

Method 2

The idea is to create separate dimension tables for each of the non-FK column of the fact table while using this column in the fact table as the FK to the newly created dimension. The idea will be explained using the semester column as an example.

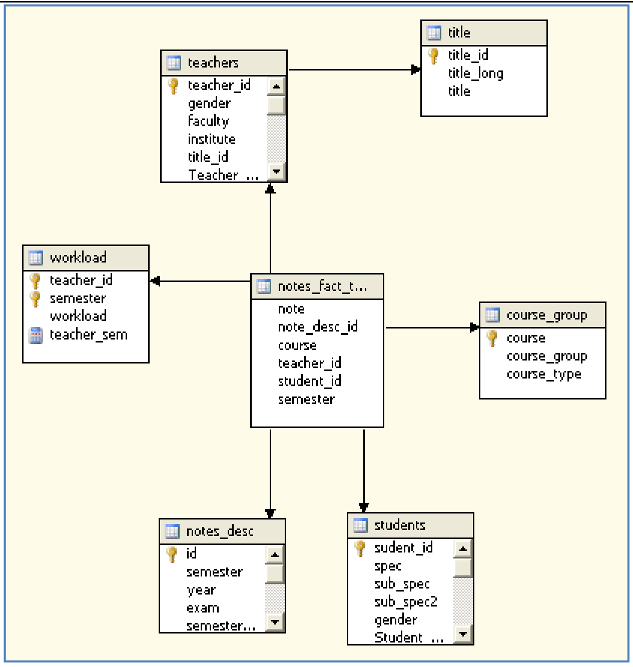
The code to create new semester dimension:

```
SELECT DISTINCT semester, other semester-related columns...
FROM notes
```

The new dimension table can be created either physically in the database (ETL script), or as an named query in Analysis Services data source view.

5 How to create a multidimensional cube?

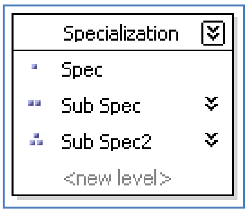
1. In SQL Server Business Intelligence Development Studio create new Analysis Services project.
2. Create a new data source (right click on Data Sources in Solution Explorer), pointing at the database created in the ETL stage. Consider selecting service account for impersonation information.
3. Create a new data source view (right click on Data Source Views), using the data source created in the previous step. Create logical FK-PK relationships between the fact table and the dimension tables (right click on a table, select New Relationship, specify fact table as the source (foreign key) table and a dimension table as the destination table). An exemplary data source view is shown below.

	 title title_id title_long title teachers teacher_id gender faculty institute title_id Teacher ... workload teacher_id semester workload teacher_sem notes_fact_t... note note_desc_id course teacher_id student_id semester course_group course course_group course_type notes_desc id semester year exam semester... students sudent_id spec sub_spec sub_spec2 gender Student ... 4. Create a new cube (right click on Cubes in Solution Explorer). Use the table notes as the measure group (i.e., fact) table, and remaining tables as dimension tables. The cube can now be built and deployed in Analysis Services instance. However, to make the cube fully functional, measures stored in the cube as well attributes and properties of dimensions should be edited (see Hints 6, 7).
6	How to add/edit measures stored in the cube? To add a new measure, right click on the Measures pane in the cube designer. When defining the measure, specify proper usage for the measure (such as sum or the number of notes, which defines how the fact variable should be aggregated when stored in the cube). See also the AggregateFunction property of the measure. Notice that only distributive measures can be defined as cube measures (such as sum or count of values of the fact variable). To provide a definition of non-distributive algebraic measure (such as the average), a calculated member should be defined for the cube (Hint 7).
7	How to add a calculated member to the cube? A calculated member allows to add an algebraic formula based on measures stored in the cube (e.g., average note based on sum and count of notes). To add a calculated member, select Calculations tab in the cube designer. Then in the right panel define name of the calculated member and an expression used to calculate it. E.g., the following expression calculates the mean note based on the two cube measures (see also left panel of Figure 5): `[Measures].[Note Sum]/[Measures].[Note Count]` Notice that while defining the formula, names of cube measures can be dragged from the Metadata pane of Calculations editor and dropped onto the Expression editor.
8	How to edit dimensions?

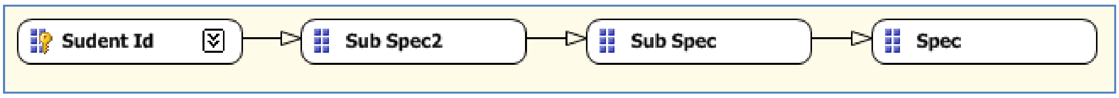
In dimensions editor, the following properties of dimensions are specified:

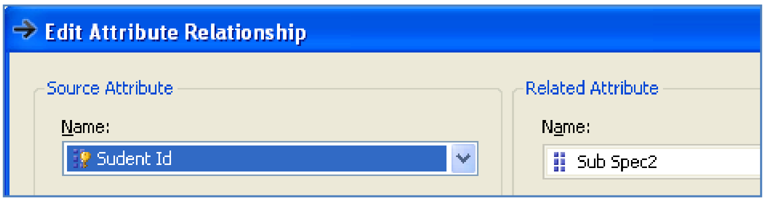
- List of attributes of the dimension,
- Drill-down hierarchies in the dimension,
- Properties of attributes related to visibility, sort order, discretization method, etc.

1. To enter dimension designer, in cube designer expand the given dimension in question (in Dimensions pane), then select command Edit dimension.
2. To design attributes of a dimension, drag and drop a column name to be used as an attribute from the Data Source View pane of dimension designer onto the Attributes pane.
3. To create drill-down hierarchies, drag attributes to be grouped onto the Hierarchies pane, as in the example shown below (Specialization hierarchy of Students dimension – see Figure 5).



4. For attributes included in a hierarchy, define attribute relationships, as shown in the example below (use Attribute Relationships tab of dimension designer).





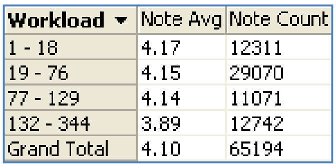
Source Attribute

Name: Sudent Id

Related Attribute

Name: Sub Spec2

5. To hide some attributes of a dimension, i.e., make them invisible for the user in OLAP browser, set the AttributeHierarchyVisible property of the attribute to False. For clarity of the multidimensional model presented to the user, attributes included in levels of drill down hierarchies are generally not shown as dimension attributes (see e.g., the Students dimension in Figure 5).
6. If members of an attribute are sorted improperly in the OLAP browser, the sort order can be changed using OrderBy attribute property.
7. For attributes with a large number of members (different values), such as the workload dimension, consider setting the DiscretizationMethod property (and related DiscretizationBucketCount property). This leads to automatic grouping of the large number of values into buckets and improves clarity of presentation, as shown below.



Workload	Note Avg	Note Count
1 - 18	4.17	12311
19 - 76	4.15	29070
77 - 129	4.14	11071
132 - 344	3.89	12742
Grand Total	4.10	65194

9	How to build / deploy / browse the cube Once designed, the cube can be built and installed on the instance of Analysis Services (server of multidimensional databases). To do this, use Build → Deploy menu command in BI Development Studio. To perform data analysis using the cube, a multidimensional OLAP browser built into the development environment can be used. To launch the browser, open MS SQL Management Studio, connect to Analysis Services, right click the cube name and select the Browse command.

Further Reading

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