

Formula Guide

STATISTICA Scorecard

STATISTICA Scorecard is a comprehensive tool dedicated for developing, evaluating, and monitoring scorecard models. For more information see *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4]. *STATISTICA Scorecard* is an add-in for *STATISTICA Data Miner* and on the computation level is based on native *STATISTICA* algorithms such as: Logistic regression, Decision trees (*CART* and *CHAID*), Factor analysis, Random forest and Cox regression. The document contains formulas and algorithms that are beyond of the scope of the implemented natively in *STATISTICA*.

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Feature selection

The *Feature Selection* module is used to exclude unimportant or redundant variables from the initial set of characteristics. Select representatives option enable you to identify redundancy among numerical variables without analyzing the correlation matrix of all variables. This module creates bundles of commonly correlated characteristics using *Factor analysis* with principal components extraction method and optional factor rotation that is implemented as standard *STATISTICA* procedure.

Bundles of variables are created based on value of factor loadings (correlation between given variable and particular factor score) User can set the option defining minimal absolute value of loading that makes given variable representative of particular factor. Number of components is defined based on eigenvalue or max factors option. If categorical predictors are selected before factor calculation variables are recoded using WoE (log odds) transformation (described in the Attribute Building chapter).

In each bundle, variables are highly correlated with the same factor (in other words have high absolute value of factor loading) and often with each other, so we can easily select only a small number of bundle representatives. After bundles are identified user can manually or automatically select representatives of each bundle. In case of automatic selection user can select correlation option that allows selecting variables with the highest correlation with other variables in given bundle. The other option is IV criterion (described below).

Variable rankings can be created using three measures of overall predictive power of variables: IV (Information Value), Cramer's V, and the Gini coefficient. Based on these measures, you can identify the characteristics that have an important impact on credit risk and select them for the next stage of model development. For more information see *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Feature selection – Cramer’s V

Cramer’s V is the measure of correlation for categorical (nominal) characteristics. This measure varies from 0 (no correlation) to 1 (ideal correlation) and can be formulated as:

$$V = \sqrt{\frac{\chi^2}{n \cdot \min(w-1, k-1)}}, \text{ in case of dichotomous dependent variable the formula is}$$

$$\text{simplified and can be expressed as } V = \sqrt{\frac{\chi^2}{n}}.$$

Notation

Where:

χ^2	chi square statistics
n	Number of cases of analyzed dataset
w	Number of categories of dependent variable
k	Number of categories of predictor variable

Computation Details

Note: All continuous predictors are categorized (using by default 10 equipotent categories). Missing data or value marked by user as atypical are considered as separate category.

Feature selection – (IV) Information Value

Information Value is an indicator of the overall predictive power of the characteristic. We

can compute this measure as: $IV = \left[\sum_{i=1}^k (g_i - b_i) \cdot \ln \left(\frac{g_i}{b_i} \right) \right] \cdot 100$

Notation

Where:

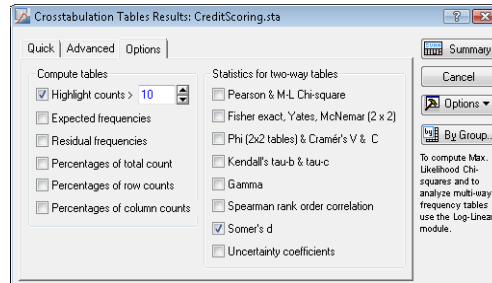
- k number of bins (attributes) of analyzed predictor
- g_i column-wise percentage distribution of the total “good” cases in the i^{th} bin
- b_i column-wise percentage distribution of the total “bad” cases in the i^{th} bin

Computation Details

Note: All continuous predictors are categorized (using by default 10 equipotent categories). Missing data or value marked by user as atypical are considered as separate category.

Feature selection – Gini

Gini coefficient equals Somer's D statistics calculated as standard *STATISTICA* procedure (see *STATISTICA Tables and Banners*).



Computation Details

Note: All continuous predictors are categorized (using by default 10 equipotent categories). Missing data or value marked by user as atypical are considered as separate category.

Interaction and Rules

Interaction and rules performs standard logistic regression with interactions (Interaction rank option) and standard Random Forest analysis (Rules option). In the Random forest – Rules generator window there are three measures allowing to assess the strength of extracted rules Bad rate, Lift(bad) and Lift (good)

In the *Interactions and rules* module, you can identify rules of credit risk which may be of specific interest and also perform interaction ranking based on logistic regression and likelihood ratio tests.

Logistic regression option checks all interactions between pairs of variables. For each pair of variables logistic regression model is built that includes such variables and interaction between them.

For each model standard *STATISTICA* likelihood ratio test is calculated comparing models with and without interaction term. Based on results (p value), the program displays interactions rank.

Using the standard *STATISTICA* Random Forest algorithm, rules of credit risk can be developed. Each terminal node in each random forest tree creates rule that is displayed for user. Based on calculated values of lift, frequency or bad rate user can select set of interesting and valuable rules. For more information see *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Tree	Variable 1	Variable 2	Frequency	Bad rate	Lift (bad)	Lift (good)	Select
1	Balance of Current A...		377	0.106	0.363	1.264	<input type="checkbox"/>
1	Balance of Current A...	Duration of Credit	271	0.336	1.148	0.939	<input type="checkbox"/>
1	Balance of Current A...	Duration of Credit	179	0.62	2.119	0.537	<input type="checkbox"/>
2	Duration of Credit	Balance of Current A...	315	0.133	0.468	1.212	<input type="checkbox"/>
2	Duration of Credit	Balance of Current A...	390	0.338	1.189	0.925	<input type="checkbox"/>
2	Duration of Credit	Balance of Current A...	51	0.137	0.482	1.206	<input type="checkbox"/>
2	Duration of Credit	Balance of Current A...	87	0.678	2.382	0.45	<input type="checkbox"/>
3	Value of Savings		280	0.168	0.573	1.177	<input type="checkbox"/>
3	Value of Savings	Amount of Credit	533	0.325	1.109	0.955	<input type="checkbox"/>
3	Value of Savings	Amount of Credit	34	0.824	2.813	0.25	<input type="checkbox"/>
4	Balance of Current A...		372	0.097	0.358	1.237	<input type="checkbox"/>
4	Balance of Current A...	Value of Savings	75	0.147	0.543	1.169	<input type="checkbox"/>
4	Balance of Current A...	Value of Savings	379	0.464	1.72	0.734	<input type="checkbox"/>
5	Balance of Current A...	Payment of Previous ...	320	0.081	0.266	1.322	<input type="checkbox"/>
5	Balance of Current A...	Payment of Previous ...	36	0.278	0.91	1.04	<input type="checkbox"/>
5	Balance of Current A...	Purpose of Credit	449	0.437	1.43	0.811	<input type="checkbox"/>

Interaction and Rules – Bad rate (and Good rate)

Bad rate shows what percent of cases that meet given rule belongs to a group of “bad”:

$BR = \frac{n_{bad}}{n_{total}}$. We can also define complementary measure – Good rate (not included in the

program interface but useful to clarify the other measures) that shows what percent of

cases that meet given rule belongs to a group of “good” $GR = \frac{n_{good}}{n_{total}}$

Notation

Where:

n_{bad}	number of “bad” cases that meet given rule
n_{good}	number of “good” cases that meet given rule
n_{total}	total number of cases that meet given rule

Interaction and Rules – Lift (bad) and Lift (good)

You can calculate Lift (bad) as a ratio between “bad rate” calculated for a subset of cases that meet given rule and “bad rate” for the whole dataset. We can express Lift(bad) using

the following formula: $Lift(bad) = \frac{BR_{Rule}}{BR_{Dataset}}$.

You can calculate Lift (good) as a ratio between “good rate” calculated for a subset of cases that meet given rule and “good rate” calculated for the whole dataset. We can express

Lift(good) using the following formula: $Lift(good) = \frac{GR_{Rule}}{GR_{Dataset}}$.

Notation

Where:

BR_{Rule}	Bad rate calculated for a subset of cases that meet given rule
$BR_{Dataset}$	Bad rate for the whole dataset
GR_{Rule}	Good rate calculated for a subset of cases that meet given rule
$GR_{Dataset}$	Good rate for the whole dataset

Attribute building

In the *Attribute Building* module, risk profiles for every variable can be prepared. Using an automatic algorithm based on the standard *STATISTICA CHAID, C&RT or CHAID on C&RT* methods; manual mode; percentiles or minimum frequency, we can divide variables (otherwise referred to characteristics) into classes (attributes or “bins”) containing homogenous risks. Initial attributes can be adjusted manually to fulfill business and statistical criteria such as profile smoothness or ease of interpretation. There is also an option to build attributes automatically. To build proper risk profiles, statistical measures of the predictive power of each attribute (Weight of Evidence (WoE) and IV – Information Value) are calculated.

If automatic creation of attributes is selected program can find optimal bins using CHAID or C&RT algorithm. In such case tree models are built for each predictor separately (in other words, each model contains only one predictor). Attributes are created based on terminal nodes prepared by particular tree. For continuous predictors there is also option CHAID on C&RT which creates initial attributes based on C&RT algorithm. Terminal nodes created by C&RT are inputs to CHAID method that tries to merge similar categories into more overall bins. All options of C&RT and CHAID methods are described in *STATISTICA Help (Interactive Trees (C&RT, CHAID))* [8]. More information see : *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Attribute building – (WoE) Weight of Evidence

Weight of Evidence (WoE) measures the predictive power of each bin (attribute). We can compute this measure as: $WoE = \ln\left(\frac{g}{b}\right) \cdot 100$.

Notation

Where:

- g column-wise percentage distribution of the total “good” cases in analyzed bin
- b column-wise percentage distribution of the total “bad” cases in the analyzed bin

Computation Details

Note: All continuous predictors are categorized (using by default 10 equipotent categories). If there are atypical values in the variables they are considered as separate bin.

Note: If there are categories without “good” or “bad” categories WoE value is not calculated. Such category should be merged with adjacent category to avoid errors in calculations.

Scorecard preparation

The final stage of this process is scorecard preparation using a standard *STATISTICA* logistic regression algorithm to estimate model parameters. Options of building logistic regression model like estimation parameters or stepwise parameters are described in *STATISTICA* Help (Generalized Linear/Nonlinear (GLZ) Models) [8].

There are also some scaling transformations and adjustment method that allows the user to calculate scorecard so the points reflect the real (expected) odds in incoming population. More information see : *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Scorecard preparation – Scaling – Factor

Factor is one of two scaling parameters used during scorecard calculation process. Factor can be expressed as: $Factor = \frac{pdo}{\ln(2)}$.

Notation

Where:

pdo Points to double the odds – parameter given by the user

Scorecard preparation – Scaling – Offset

Offset is one of two scaling parameters used during scorecard calculation process. Offset can be expressed as: $Offset = Score - (Factor \cdot \ln(Odds))$

Notation

Where:

- Score* scoring value for which you want to receive specific odds of the loan repayment - parameter given by the user
- Odds* odds of the loan repayment for specific scoring value - parameter given by the user
- Factor* scaling parameter calculated on the basis of formula presented above

Scorecard preparation – Scaling – Calculating score (WoE coding)

When WoE coding is selected for given characteristic, score for each bin (attribute) of such

characteristic is calculated as: $Score = \left(\beta \cdot WoE + \frac{\alpha}{m} \right) \cdot factor + \frac{offset}{m}$.

Notation

Where:

β logistic regression coefficient for characteristics that owns the given attribute

α logistic regression intercept term

WoE Weight of Evidence value for given attribute

m number of characteristics included in the model

$factor$ scaling parameter based on formula presented previously

$offset$ scaling parameter based on formula presented previously

Computation Details

Note: After computation is complete the resulting value is rounded to the nearest integer value.

Scorecard preparation – Scaling – Calculating score (Dummy coding)

When dummy coding is selected for given characteristic, score for each bin (attribute) of

such characteristic is calculated as: $Score = \left(\beta + \frac{\alpha}{m} \right) \cdot factor + \frac{offset}{m}$.

Notation

Where:

β	logistic regression coefficient for the given attribute
α	logistic regression intercept term
m	number of characteristics included in the model
<i>factor</i>	scaling parameter based on formula presented previously
<i>offset</i>	scaling parameter based on formula presented previously

Computation Details

Note: After computation is complete the resulting value is rounded to the nearest integer value.

Scorecard preparation – Scaling – Neutral score

Neutral score is calculated as: $Neutral\ score = \sum_{i=1}^k score_i \cdot distr_i$.

Notation

Where:

k number of bins (attributes) of the characteristic

$score_i$ scoring assigned to the i^{th} bin

$distr_i$ percentage distribution of the total cases in the i^{th} bin

Scorecard preparation – Scaling – Intercept adjustment

Balancing data do not effect on regression coefficient except of the intercept (see: Maddala [3] s. 326). To make score reflect the real data proportions, intercept adjustment is performed using the following formula: $\alpha_{adjusted} = \alpha_{regression} - (\ln(p_{good}) - \ln(p_{bad}))$. After adjustment, calculated intercept value is used during scaling transformation.

Notation

Where:

- $\alpha_{regression}$ logistic regression intercept term before adjustment
- p_{good} probability of sampling cases from “good” strata (or class that is coded in logistic regression as 1)
- p_{bad} probability of sampling cases from “bad” strata (or class that is coded in logistic regression as 0)

Survival

The *Survival* module is used to build scoring models using the standard *STATISTICA* Cox Proportional Hazard Model. We can estimate a scoring model using additional information about the time of default, or when a debtor stopped paying. Based on this module, we can calculate the probability of default (scoring) in given time (e.g., after 6 months, 9 months, etc.). Options of input parameters and output products of Cox Proportional Hazard Model are described in *STATISTICA* Help (Advanced Linear/Nonlinear Models - Survival - Regression Models) [8]. For more information see *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Reject Inference

The *Reject inference* module allows you to take into consideration cases for which the credit applications were rejected. Because there is no information about output class (good or bad credit) of rejected cases, we must add this information using an algorithm. To add information about the output class, the standard *STATISTICA* *k*-nearest neighbors method (from menu Data-Data filtering/Recoding-MD Imputation) and parceling method are available. After analysis, a new data set with complete information is produced.

Reject Inference - Parceling method

To use this method preliminary scoring must be calculated for accepted and rejected cases. After scoring is calculated you must divide score values into certain group with the same score range. *Step* option allows you to divide score into group with certain score range and starting point equal to *Starting value* parameter, *Number of intervals* creates given number of equipotent groups. In each of the groups number of bad and good cases is calculated, next rejected cases that belong to this score range group are randomly labeled as “bad” or “good” proportionally to the number of accepted “good” and “bad” in this range.

Business rules often suggest that the ratio of good to bad in a group of rejected applications should not be the same as in the case of applications approved. User can manually change the proportion of “good” and “bad” rejected labeled cases in each score range group separately. One of the rules of thumb suggests that the rejected bad rate should be from two to four times higher than accepted.

Model evaluation

The *Model Evaluation* module is used to evaluate and compare different scorecard models. To assess models, the comprehensive statistical measures can be selected, each with a full detailed report. More information see : *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Model evaluation – Gini

Gini coefficient measures the extent to which the variable (or model) has better classification capabilities in comparison to the variable (model) that is a random decision maker. Gini has a value in the range [0, 1], where 0 corresponds to a random classifier, and 1 is the ideal classifier. We can compute Gini measure as:

$$G = \left| 1 - \sum_{i=1}^k (B(x_i) - B(x_{i-1})) \cdot (G(x_i) + G(x_{i-1})) \right|; \text{ and } G(x_0) = B(x_0) = 0$$

Notation

Where:

- k number of categories of analyzed predictor
- $G(x_i)$ cumulative distribution of “good” cases in the i^{th} category
- $B(x_i)$ cumulative distribution of “bad” cases in the i^{th} category

Computation Details

Note: There is strict relationship between Gini coefficient as AUC (Area Under ROC Curve) coefficient. Such relationship can be expressed as $G = 2 \cdot AUC - 1$.

Model evaluation – Information Value (IV)

Information Value (IV) measure is presented in the previous section ([feature selection](#)) of this document.

Model evaluation - Divergence

You can express this index using the following formula: $Divergence = \frac{(mean_G - mean_B)^2}{0,5 \cdot (var_G + var_B)}$.

Notation

Where:

- $mean_G$ the mean value of the score in “good” population
- $mean_B$ the mean value of the score in “bad” population
- var_G the variance of the score in “good” population
- var_B the variance of the score in “bad” population

Model evaluation – Hosmer-Lemeshow

Hosmer-Lemeshow goodness of fit statistic is calculated as:
$$HL = \sum_{i=1}^k \frac{(o_i - n_i \cdot \bar{\pi}_i)^2}{n_i \cdot \bar{\pi}_i \cdot (1 - \bar{\pi}_i)}$$

Notation

Where:

k	number of groups
o_i	number of “bad” cases in the i^{th} group
n_i	number of cases in the i^{th} group
$\bar{\pi}_i$	average estimated probability of “bad” in the i^{th} group

Computation Details

Groups for this test are based on the values of the estimated probabilities. In STATISTICA Scorecard implementation 10 groups are prepared. Groups have the same number of cases. First group contains subjects having the smallest estimated probabilities and consistently the last group contains cases having the largest estimated probabilities.

Model evaluation – Kolmogorov-Smirnov statistic

Kolmogorov-Smirnov (KS) statistic is determined by the maximum difference between the cumulative distribution of good and bad cases. You can calculate KS statistic using the following formula: $KS = \max_j |G(x_j) - B(x_j)|$

Notation

Where:

$G(x)$ cumulative distribution of “good” cases.

$B(x)$ cumulative distribution of “bad” cases

x_j j-th distinct value of score

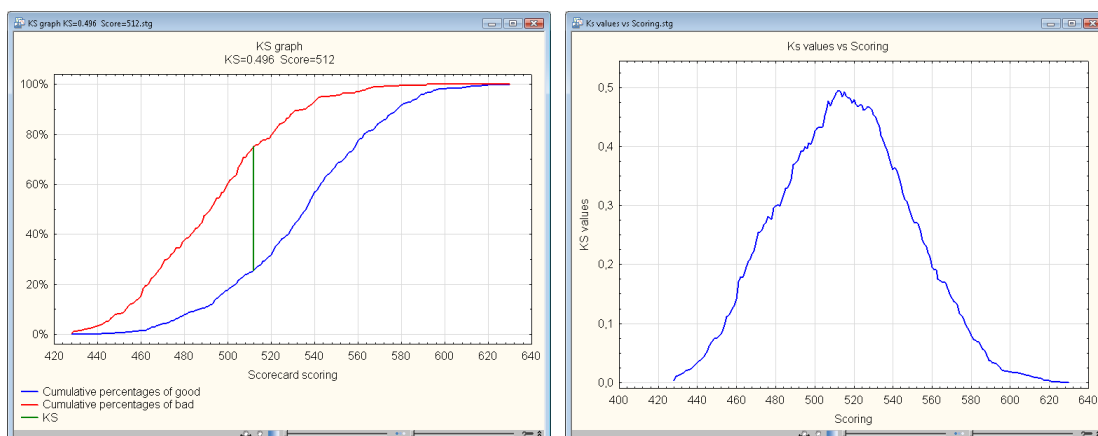
$j=1, \dots, N$ where N is the number of distinct score values

Computation Details

KS statistic is a base of formulating statistical test checking if tested distributions differs significantly. In *STATISTICA Scorecard* standard KS test is performed based on standard *STATISTICA* implementation.

Comments

Very often KS statistic is presented in the graphical form such as on graphs below.



For more information see TUTORIAL Developing Scorecards Using *STATISTICA* Scorecard [4].

Model evaluation – AUC – Area Under ROC Curve

AUC measure can be calculated on the basis of Gini coefficient and can be expressed as:

$$AUC = \frac{G+1}{2}.$$

Notation

Where:

G Gini coefficient calculated for analyzed model

Model evaluation – 2x2 tables measures

AUC measure report generates set of 2x2 table (confusion matrix) effect measures such as sensitivity, specificity, accuracy and other measures. Let's assume that "bad" cases will be considered as positive test results and "good" cases as negative test results. Based on this assumption we can define confusion matrix as below.

		Observed	
		Bad	Good
Predicted	Bad	True Positive (TP)	False Positive (FP)
	Good	False Negative (FN)	True Negative (TN)

Based on such confusion matrix Sensitivity can be expressed as: $SENS = \frac{TP}{TP + FN}$, whereas

specificity can be expressed as $SPEC = \frac{TN}{TN + FP}$. The other measures used in the AUC

report : $ACC = \frac{TP + TN}{TP + TN + FP + FN}$; $PPV = \frac{TP}{TP + FP}$; $NPV = \frac{TN}{TN + FN}$; $LR = \frac{SENS}{1 - SPEC}$.

Notation

Where:

<i>TP</i>	Number of bad cases that are correctly predicted as bad
<i>FP</i>	Number of good cases that are incorrectly predicted as bad
<i>FN</i>	Number of bad cases that are incorrectly predicted as good
<i>TN</i>	Number of good cases that are correctly predicted as good
<i>SENS</i>	Sensitivity
<i>SPEC</i>	Specificity
<i>ACC</i>	Accuracy
<i>PPV</i>	Positive predictive value
<i>NPV</i>	Negative predictive value
<i>LR</i>	Likelihood ratio (+)

Cut-off point selection

The *Cut off point* selection module is used to define the optimal value of scoring that separates accepted and rejected applicants. You can extend the decision procedure by adding one or two additional cut-off points (e.g., applicants with scores below 520 will be declined, applicants with scores above 580 will be accepted, and applicants with scores between these values will be asked for additional qualifying information). Cut-off points can be defined manually, based on a Receiver Operating Characteristic (ROC) analysis for custom misclassifications costs and bad credit fraction. (ROC analysis provides a measure of the predictive power of a model). Additionally, we can set optimal cut-off points by simulating profit, associated with each cut-point level. Goodness of the selected cut-off point can be assessed based on various reports. More information see : *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Cut-off point selection – ROC optimal cut-off point

ROC optimal cut-off point is defined as the point tangent to the line with the slope

calculated using the following formula: $m = \frac{FP \text{ cost}}{FN \text{ cost}} \cdot \frac{1-p}{p}$

Notation

Where:

- p prior probability of “bad” cases in the population.
- $FP \text{ cost}$ cost of situation when “good “cases that are incorrectly predicted as “bad”
- $FN \text{ cost}$ cost of situation when “bad “cases that are incorrectly predicted as “good”

Score cases

The *Score Cases* module is used to score new cases using a selected model saved as an XML script. We can calculate overall scoring, partial scorings for each variable, and probability of default from the logistic regression model, adjusted by an *a priori* probability of default for the whole population supplied by the user. For more information see *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Score cases – Adjusting probabilities

To adjust the posterior probability the following formula is used:

$$p_i^* = \frac{p_i \cdot \rho_0 \cdot \pi_1}{(1 - p_i) \cdot \rho_1 \cdot \pi_0 + p_i \cdot \rho_0 \cdot \pi_1}$$

Notation

Where:

p_i	unadjusted estimate of posterior probability
ρ_0	proportion of “good” class in the sample
ρ_1	proportions of “bad” class in the sample
π_0	proportions of “good” class in the population
π_1	proportion of “bad” class in the population

Calibration tests

The *Calibration Tests* module allows banks to test whether or not the forecast probability of default (PD) has been the PD that has actually occurred. The Binomial Distribution and Normal Distribution tests are included to test as appropriate the rating classes. The Austrian Supervision Criterion (see [5]) can be selected allowing *STATISTICA* to automatically choose the appropriate distribution test.

Computation Details

Two tests for determining whether a model underestimates rating results or the PD are the standard *STATISTICA* Normal Distribution Test and the standard *STATISTICA* Binomial Test. When the Austrian Supervision Criterion is checked, *STATISTICA* automatically selects the proper test for each rating class. (see [5]). If the sample meets the following criteria, the Standard Normal Distribution test is appropriate. For example, if you have a maximum PD value for a class of .10% then your minimum frequency for that class must be greater than or equal to 9,010 cases to use the Normal Distribution test. If there are less than 9,101 cases, the Binomial Distribution test would be appropriate.

Maximum PD Value	Minimum Class Frequency
0.10%	9,010
0.25%	3,610
0.50%	1,810
1.00%	910
2.00%	460
3.00%	310
5.00%	190
10.00%	101
20.00%	57
50.00%	37

Population stability

The *Population Stability* module provides analytical tools for comparing two data sets (e.g., current and historical data sets) in order to detect any significant changes in characteristic structure or applicant population. Significant distortion in the current data set may provide a signal to re-estimate model parameters. This module produces reports of population and characteristic stability with respective graphs. For more information see *TUTORIAL Developing Scorecards Using STATISTICA Scorecard* [4].

Population stability

Population stability index measures the magnitude of the population shift between actual and expected applicants. You can express this index using the following formula:

$$Population\ stability = \sum_{i=1}^k (Actual_i - Expected_i) \cdot \ln\left(\frac{Actual_i}{Expected_i}\right).$$

Notation

Where:

k number of different score values or score ranges

$Actual_i$ percentage distribution of the total “Actual” cases in the i^{th} score value or score range

$Expected_i$ percentage distribution of the total “Expected” cases in the i^{th} score value or score range

Characteristic stability

Characteristic stability index provides the information on shifts of distribution of variables used for example in the scorecard building process. You can express this index using the

following formula: $Characteristic\ stability = \sum_{i=1}^k (Actual_i - Expected_i) \cdot score_i$.

Notation

Where:

k number of categories of analyzed predictor

$Actual_i$ percentage distribution of the total “Actual” cases in the i^{th} category of characteristic

$Expected_i$ percentage distribution of the total “Expected” cases in the i^{th} category of characteristic

$score_i$ value of the score for the i^{th} category of characteristic

References

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