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Retailer Segmentation via NeXClass Ordered Multi-criteria Classification Methodology and System

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***Abstract**:*
NexClass is a multi-criteria methodology and decision support system developed to support multi-criteria classification into predefined nominal (non-ordered) categories. In this paper we introduce an extension of NexClass methodology at classification problems ordinal (ordered) categories. For each category an entrance threshold is defined by decision maker, which indicates its boundary with respect to the evaluation criteria. Then, assignment of alternatives into the classes is based on the concept of non-exclusivity. This defines at what degree an alternative can be included into a specific category. Alternatives are evaluated according to the evaluation criteria, and non-excluding degrees are calculated for each category. Finally, alternatives are assigned into the category for which non-excluding degree gets the minimum value. The NexClass decision support system implements the above classification algorithm, providing a user-friendly interface. This work presents the methodology and the classification model along with a real world application to retailer segmentation. Findings show that the methodology is valid and can be used for segmentation problems in marketing or relevant domains.

Keywords: *Multi-criteria classification, decision support system, NexClass*

1. Introduction

Assignment of actions (numbers, people, etc) into appropriate categories is a common decision making problem at various domains, including finance, medical diagnosis, human resources management, marketing, pattern recognition and production management among others [1], [2], [3], [4], [5], [6], [7], [18].

Classification is divided in supervised that requires decision maker's contribution, and unsupervised, which is performed automatically and does not require decision maker's contribution. We refer to supervised as sorting or classification, depending on whether categories are ordered or not, while we refer to unsupervised as clustering. Multi-criteria analysis offers a variety of methodologies and tools for sorting problems, as well as ranking ones [13], [14], [15], [16]. NeXClass is a classification algorithm and a decision support system for classification problems based on multi-criteria analysis, which solves classification problems to predefined nominal (non-ordered) categories [8], [9], [10], [11], [12].

In this paper we present an extension to the NeXClass algorithm for classification of alternatives into ordered categories, along with the decision support system. The algorithm is based on outranking relations and the concept of category entrance threshold. In general, for each predefined category, decision maker uses available information and defines an entrance threshold. The threshold represents the minimum requirements for an alternative, in terms of performance on the evaluation criteria, in order to be included in this category. Decision makers define alternatives' performance on the criteria as well as all required parameters' values. For each alternative, its performance on the criteria is compared with the entrance threshold of every category and finally the alternative is assigned to the category for which it has the maximum distance from the entrance threshold.

Following the introduction (Section 1), we introduce the NeXClass algorithm and the classification methodology (Section 2). Next, the NeXClass decision support system is presented (Section 3), and in Section 4 we apply the methodology in retailer segmentation to demonstrate the decision support system usage. The paper concludes with discussion derived from DSS and methodology application (Section 5).

2. NeXClass Methodology

2.1. Overview

In order to support classification decisions to ordinal categories, we developed classification algorithm, based on NeXClass algorithm, using multi-criteria analysis and outranking relations [19], [17]. Given a set of alternatives, a set of predefined ordinal categories and a set of evaluation criteria, we want to classify an alternative into a specific category with respect to its performance on the evaluation criteria. Initially, we define the 'non-excluding principle', as the basic classification rule of alternatives to categories as following:

- An alternative ‘a’ is assigned to a category if it is ‘not excluded’ or ‘roughly not excluded’ according to the entrance threshold of this category.

In order to utilize the rule to assign alternatives to categories we define the ‘excluding degree’ as the degree of validation of the statement:

- Alternative ‘a’ is not-excluded or roughly not-excluded

‘Excluding degree’ measures at what degree the alternative is not excluded from a category or equivalently at what degree the alternative’s performance overcomes the category entrance threshold. Calculation of the degree thus results in the following cases:

- The more the alternative performance overcomes the entrance threshold, the more likely it can be assigned to the category. In this case ‘excluding degree’ is minimized.
- The less the alternative performance overcomes the entrance threshold, the less likely it can be assigned to the category. In this case ‘excluding degree’ is maximized.

Finally, an alternative is assigned to the category for which the ‘excluding degree’ is the minimum.

For a structured approach to classification problems, we follow an integrated methodology, which is separated in three main phases:

- Problem formulation. In this phase the decision maker defines all necessary parameters.
- NexClass algorithm application. The algorithm classifies the alternatives.
- Result validation. In this phase the results are examined according to the parameters defined in the problem formulation phase.

2.2. NexClass Algorithm

Notations

$A=\{a_1,a_2,...,a_m\}$: a set of alternatives for classification,

$G=\{g_1,g_2,...,g_n\}$: a set of evaluation criteria,

$C=\{C^1,C^2,...,C^h\}$: a set of categories,

$B^h=\{b_1^h,b_2^h,...,b_k^h\}$: a set of prototypes for category h, where $B^h=\{b_i^h \mid i=1,..k,h=1,...L_h\}$ and b_i^h is the i_{th} prototype of h_{th} category. These prototypes define the category as thresholds of entrance to category.

Alternatives’ performance on criteria is calculated in way such that $\forall a, g(a)=(g_1(a),g_2(a),...,g_n(a))$ and $\forall b_i^h, g(b_i^h)=(g_1(b_i^h),g_2(b_i^h),...,g_n(b_i^h))$.

Excluding degree definition

In order to estimate the degree of validation of the statement

‘Alternative $a\in A$ is not excluded or is not roughly excluded’,

An appropriate degree has to be defined. Instead of the above statement, we can use the following equivalent:

‘Alternative $a\in A$ is preferred or roughly preferred over the entrance threshold’,

and estimate the degree of validation of this one, or the preference degree of an alternative $a\in A$ over the category C^h entrance threshold b_i^h.

In order to estimate the degree of validation of the above statement, we utilize outranking relations. So, an alternative is preferred over the entrance threshold if

$$aPb_i^h \Leftrightarrow aSb_i^h \wedge \neg b_i^h Sa$$

Degrees of validation of aSb_i^h and b_i^hSa are given by the credibility indexes $\gamma_i\,(a,b_i^h)$ and $\gamma_i\,(b_i^h,a)$.

So, maximization of preference of alternative $a\in A$ over the entrance threshold b_i^h occurs when $\gamma_i\,(a,b_i^h)\longrightarrow 1$ and $\gamma_i\,(b_i^h,a)\longrightarrow 0$.

On the other hand, minimization of preference of alternative $a\in A$ over the entrance threshold b_i^h occurs when $\gamma_i\,(a,b_i^h)\longrightarrow 0$ and $\gamma_i\,(b_i^h,a)\longrightarrow 1$.

In order to estimate the degree of preference of alternative $a\in A$ over the entrance threshold b_i^h we define the ‘excluding degree’ as

$$\gamma_i^{tot}=\frac{\gamma_i\,(b_i^h,a)}{1+\gamma_i\,(a,b_i^h)}\in[0,1]$$

where $\gamma_i\,(a,b_i^h)$ and $\gamma_i\,(b_i^h,a)$ are the degrees of validation of aSb_i^h and b_i^hSa statements.

When $\gamma_i^{tot}\longrightarrow 0$ ‘excluding degree’ of alternative $a\in A$ over the entrance threshold b_i^h is maximized, while when $\gamma_i^{tot}\longrightarrow 1$ ‘excluding degree’ of alternative $a\in A$ over the entrance threshold b_i^h is minimized.

Defined in this way, 'excluding degree' expresses the degree of validation of the statement '*Alternative* $a \in A$ *is preferred or roughly preferred over the entrance threshold*', or the equivalent '*Alternative* $a \in A$ *is not excluded or is not roughly excluded*'. When the excluding degree is maximized, alternative is less preferred over the entrance threshold and excluded, while when it is maximized alternative is more preferred over the entrance threshold and included.

Excluding degree calculation

Calculation of excluding degree $\gamma_i^{tot} = \dfrac{\gamma_i\,(b_i^h, a)}{1+\gamma_i\,(a, b_i^h)}$ is based on outranking relations. Expressions $\gamma_i\,(a, b_i^h)$ and $\gamma_i\,(b_i^h, a)$ are the degrees of validation of the statements aSb_i^h and $b_i^h Sa$ respectively, and are calculated by the concordance and discordance indexes from the following expressions

$$\gamma_i\,(a,b_i^h) = \begin{cases} \mathrm{C}(\mathrm{a}, b_i^h) & \text{if} \quad \mathrm{d_i}(\mathrm{a}, b_i^h) < \mathrm{C}(\mathrm{a}, b_i^h) \\ \mathrm{C}(\mathrm{a}, b_i^h) \prod \dfrac{1-d_i(a,b_i^h)}{1-C(a,b_i^h)} & \textit{otherwise} \end{cases}$$

$$\gamma_i\,(b_i^h,a) = \begin{cases} \mathrm{C}(b_i^h, a) & \text{if} \quad \mathrm{d_i}(b_i^h, a) < \mathrm{C}(b_i^h, a) \\ \mathrm{C}(b_i^h, a) \prod \dfrac{1-d_i(b_i^h,a)}{1-C(b_i^h,a)} & \textit{otherwise} \end{cases}$$

respectively.

Concordance [$C(a,b_i^h)$, $C(b_i^h,a)$] and discordance [$d(a,b_i^h)$, $d(b_i^h,a)$] indexes are calculated.

Total concordance index is calculated as

$$C(a,b_i^h) = \sum_{i=1}^{n} w_i c_i (a,b_i^h)$$

$$C(b_i^h,a) = \sum_{i=1}^{n} w_i c_i (b_i^h,a)$$

where partial concordance and discordance indexes for ascending criteria values are calculated as following:

$$c_i(a,b_i^h) = \begin{cases} 0 & g_i\,(a) \le g_i\,(b_i^h) - p_i(b_i^h) \\ \dfrac{g_i\,(a) - g_i\,(b_i^h) + p_i(b_i^h)}{p_i(b_i^h) - q_i(b_i^h)} & g_i\,(a) \in (\,g_i\,(b_i^h) - p_i(b_i^h), g_i\,(b_i^h) - q_i(b_i^h)\,] \\ 1 & g_i\,(a) > g_i\,(b_i^h) - q_i(b_i^h) \end{cases}$$

$$c_i(b_i^h,a) = \begin{cases} 0 & g_i\,(a) \ge g_i\,(b_i^h) + p_i(b_i^h) \\ \dfrac{g_i\,(b_i^h) - g_i\,(a) + p_i(b_i^h)}{p_i(b_i^h) - q_i(b_i^h)} & g_i\,(a) \in [\,g_i\,(b_i^h) + q_i(b_i^h), g_i\,(b_i^h) + p_i(b_i^h)\,) \\ 1 & g_i\,(a) < g_i\,(b_i^h) + q_i(b_i^h) \end{cases}$$

$$d_i(a,b_i^h) = \begin{cases} 0 & g_i\,(a) > g_i\,(b_i^h) - p_i(b_i^h) \\ \dfrac{g_i\,(b_i^h) - g_i\,(a) - p_i(b_i^h)}{v_i(b_i^h) - q_i(b_i^h)} & g_i\,(a) \in (\,g_i\,(b_i^h) - v_i(b_i^h), g_i\,(b_i^h) - p_i(b_i^h)\,] \\ 1 & g_i\,(a) \le g_i\,(b_i^h) - v_i(b_i^h) \end{cases}$$

$$d_i(b_i^h,a) = \begin{cases} 0 & g_i\,(a) \le g_i\,(b_i^h) + p_i(b_i^h) \\ \dfrac{g_i\,(a) - g_i\,(b_i^h) - p_i(b_i^h)}{v_i(b_i^h) - p_i(b_i^h)} & g_i\,(a) \in (\,g_i\,(b_i^h) + p_i(b_i^h), g_i\,(b_i^h) + v_i(b_i^h)\,] \\ 1 & g_i\,(a) > g_i\,(b_i^h) + v_i(b_i^h) \end{cases}$$

while for descending are calculated as following:

$$c_i(a,b_i^h) = \begin{cases} 0 & g_i\,(a) \ge g_i\,(b_i^h) + p_i(b_i^h) \\ \dfrac{g_i\,(b_i^h) - g_i\,(a) + p_i(b_i^h)}{p_i(b_i^h) - q_i(b_i^h)} & g_i\,(a) \in [\,g_i\,(b_i^h) + q_i(b_i^h), g_i\,(b_i^h) + p_i(b_i^h)\,) \\ 1 & g_i\,(a) < g_i\,(b_i^h) + q_i(b_i^h) \end{cases}$$

$$c_i(b_i^h,a) = \begin{cases} 0 & g_i\,(a) \le g_i\,(b_i^h) - p_i(b_i^h) \\ \dfrac{g_i\,(a) - g_i\,(b_i^h) + p_i(b_i^h)}{p_i(b_i^h) - q_i(b_i^h)} & g_i\,(a) \in [\,g_i\,(b_i^h) - p_i(b_i^h), g_i\,(b_i^h) - q_i(b_i^h)\,) \\ 1 & g_i\,(a) > g_i\,(b_i^h) - q_i(b_i^h) \end{cases}$$

$$d_i(a,b_i^h) = \begin{cases} 0 & g_i\,(a) \le g_i\,(b_i^h) + p_i(b_i^h) \\ \dfrac{g_i\,(a) - g_i\,(b_i^h) - p_i(b_i^h)}{v_i(b_i^h) - p_i(b_i^h)} & g_i\,(a) \in (\,g_i\,(b_i^h) + p_i(b_i^h), g_i\,(b_i^h) + v_i(b_i^h)\,] \\ 1 & g_i\,(a) > g_i\,(b_i^h) + v_i(b_i^h) \end{cases}$$

$$d_i(b_i^h,a) = \begin{cases} 0 & g_i\,(a) > g_i\,(b_i^h) - p_i(b_i^h) \\ \dfrac{g_i\,(b_i^h) - g_i\,(a) - p_i(b_i^h)}{v_i(b_i^h) - p_i(b_i^h)} & g_i\,(a) \in (\,g_i\,(b_i^h) - v_i(b_i^h), g_i\,(b_i^h) - p_i(b_i^h)\,] \\ 1 & g_i\,(a) \le g_i\,(b_i^h) - v_i(b_i^h) \end{cases}$$

Fuzzy excluding degree calculation

In a more general setting, entrance thresholds of a category $C^h \in \Omega$ can be more than one.

We define the fuzzy excluding degree, of an alternative $a \in A$ over a category $C^h \in \Omega$ as

$\gamma(a,C^h) = P(a,b^h) = \gamma^{tot}$ for the case of one entrance threshold for the category.

In the case of more than on entrance thresholds, expression $\gamma_i^{tot} = \dfrac{\gamma(b_i^h, a)}{1+\gamma(a,b_i^h)}$ is calculated for every threshold for the category b_i^h and the fuzzy excluding degree is defined as

$$\gamma(a,C^h) = \min\{P(a,b_1^h), P(a,b_2^h),..., P(a,b_k^h)\} = \min\{\gamma_1^{tot}, \gamma_2^{tot},..., \gamma_k^{tot}\}$$

Fuzzy excluding degree in the case of one threshold expresses the degree of preference of alternative $a \in A$ over the entrance threshold b^h, while in the case of more thresholds, it expresses the degree of preference of alternative $a \in A$ over the threshold b_i^h for which the excluding degree is the minimum.

Assignment into categories

Having calculated the fuzzy excluding degree of an alternative $a \in A$ for every category $\{C^1, C^2,..., C^h\}$, assignment to one category is based on the following rule:

$$a \in C^h \Leftrightarrow \gamma(a,C^h) = \min\{\gamma(a,C^i) / i \in \{1,...,k\}\}$$

which states that alternative $a \in A$ is assigned to the category $C^h \in \Omega$ for which the excluding degree over the entrance threshold is minimum.

2.3. Classification Methodology

The application of the algorithm for classification problems is comprised of the following phases:

Problem definition: Decision maker formulates the problem, setting all appropriate parameters. In details, DM defines the set of categories $\Omega = \{C^1, C^2,..., C^h\}$ for the classification of alternatives, the set of evaluation criteria $F = \{g_1, g_2,..., g_n\}$, the criteria weights, the set of alternatives $A = \{a_1, a_2,..., a_m\}$ for classification, and their performance on the evaluation criteria $\forall a, g(a) = (g_1(a), g_2(a),..., g_n(a))$.

Next DM defines appropriate entrance thresholds for each category $\Omega = \{C^1, C^2,..., C^h\}$ and for each threshold defines preference, indifference and veto thresholds.

NeXClass application: Following the formulation, NeXClass algorithm is applied to the training set initially, and results are evaluated by the DM. In case of misclassifications, DM redefines parameters in order to calibrate the model. While training set classification is acceptable, the entire set of alternatives is classified.

Results assessment: The DM assesses the results, and in case of major misclassifications, modifies the parameters accordingly and reruns the model.

3. NexClass Decision Support System

The algorithm is implemented in NeXClass DSS, a Decision Support System which was developed in order to support decision makers to interactively solve classification problems. The DSS was developed in C++ and is currently running under Windows OS. In this paper, we present the updated version which supports the modified classification algorithm. The DSS provides the following main functionalities:

- User management: This module provides user authentication procedure and in the case of multiple users, restricts access only to user's own models.
- Configuration: This module provides general configuration capabilities to user to customize the DSS interface, such as font selection, sizing, colour, and other interface parameters.
- Model import: In the case of large quantities of data, a user can import a model from a data source, instead of inserting all the values manually. In this case, the module imports all the data from the external source and formats the classification model.
- Model creation: In the general case, a user creates a new model from scratch. This module provides all the functionality to create a new model following the steps of the problem definition phase of the methodology.
- Model reporting: After the model creation/import, this module provides overview of the model, allowing corrections to it.
- Classification: This is the module which implements the classification algorithm, either on a training set or the set of the alternatives.
- Results reporting: After the classification, this module presents the results in appropriate format. Results include not only the alternatives' assignment to classes, but evaluations of excluding degrees, concordance and discordance indexes as mentioned in the methodology.

4. Nexclass Application to Classification of Retailers

4.1. Overview

In the following, we present a real world application of the classification methodology as well as the NeXClass DSS in order to demonstrate the usage of both methodology and DSS in real world. The problem refers to retailer classification for a targeted marketing campaign related to a new product promotion. Retailer evaluation is an important decision problem for the campaign's success and candidate retailers must be selected according to a number of carefully selected criteria.

Working in collaboration with a specific marketing agency we developed a framework for retailer evaluation aiming to support decision maker throughout the entire decision process. Since the desirable output of the decision process was the classification of retailers to several predefined ordered groups according to specific criteria, NeXClass method was selected for the analysis and construction of the decision process. In brief, several semi-structured questionnaires were used to define criteria for retailer evaluation. Next, a number of categories were defined for the classification of retailers. An expert was asked to assign weights to the criteria and define and estimate valid measures for usage from the DSS. A number of experiments were executed using an existing retailer base and classification results were compared with classification deriving from the existing decision process.

4.2. Problem Definition

Following the steps of NeXClass methodology, a classification problem was formulated and agency's expert defined required parameters reflecting decision preferences (Table 1). Analyzing existing retailer base some key merchant characteristics were identified that can be used in order to define two major. These segments represent a segmentation of the relevant market in terms of site potential and profitability for a retailer.

Segment 1 represents retailers with low profitability and weak positioning. This segment includes merchants with varying operation periods and not stable customer base. They perform low transaction volumes for more than 50% annually. The location and overall potential is relatively low and they are not profitable on a continuous basis.

Segment 2 represents retailers with high profitability and strong positioning. This segment includes merchants with stable operation over periods and stable customer base. These merchants present high transaction volumes for more than 50% annually. The location and overall site potential is quite strong and they are the most profitable of all.

Segment 1	Segment 2
Low • volume of transactions, • profitability, • site potential	High • volume of transactions, • profitability, • potential

Table 1: Segmentation Matrix

Based on the segmentation, two categories, reflecting the relevant retailer importance, were defined (Table 2) and linked to specific marketing strategy each.

	C1	C2
Definition	**Super Stars**	**Low expectations**
Strategy	• High expenditure level, • Aggressive, • Allocate maximum available resources	• Low expenditure level, • Conservative, • Resources on a step by step basis

Table 2: Retailer Categories

Criteria definition: The next step was to define a set of appropriate evaluation criteria. The criteria definition as well as their scale was based on expert's opinion reflecting the most important aspects of retailers' performance (Table 3).

	Definition	Scale
G1	Retailer size (average daily sales in 1.000Euros)	1-100
G2	Intensity of electronic channels usage (per cent of daily sales)	1-100
G3	Average value per sale (in Euros)	1-100
G4	Average growth rate. Indicator showing increase in transaction ratio	1-100
G5	Competition and Location factor based on statistical data	1-100

Table 3: Criteria

Criteria weights: Based on the above, the expert defined criteria weights (Table 4) and set the values to the DSS (Fig. 1).

	G1	G2	G3	G4	G5
Weights	20.00	15.00	45.00	10.00	10.00

Table 4: Criteria Weights

4.3. Categories Profiles

Next, the expert defined the limits of the categories setting appropriate values for each criterion in the scales defined previously (Table 5) and set the values to the DSS (Figure 2).

	G1	G2	G3	G4	G5
C1	14.00	32.00	47.00	72.00	85.00
Indiff	1.00	1.00	2.00	2.00	3.00
Pref	4.00	3.00	5.00	5.00	6.00
Veto	20.00	20.00	20.00	20.00	20.00
C2	4.00	8.00	12.00	21.00	32.00
Indiff	1.00	1.00	2.00	2.00	3.00
Pref	4.00	3.00	5.00	5.00	6.00
Veto	20.00	20.00	20.00	20.00	20.00

Table 5: Category Profiles

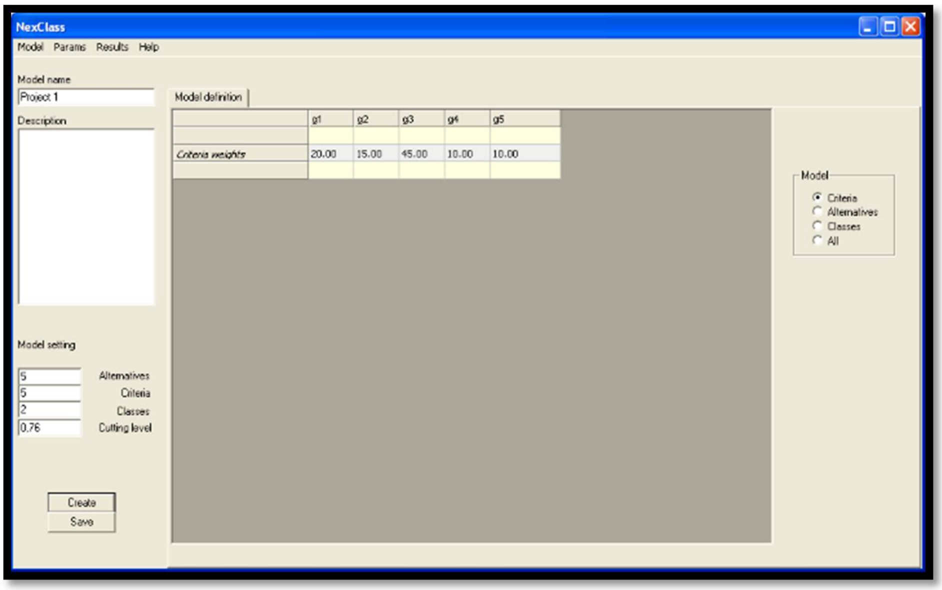

Figure 1: Criteria Definition

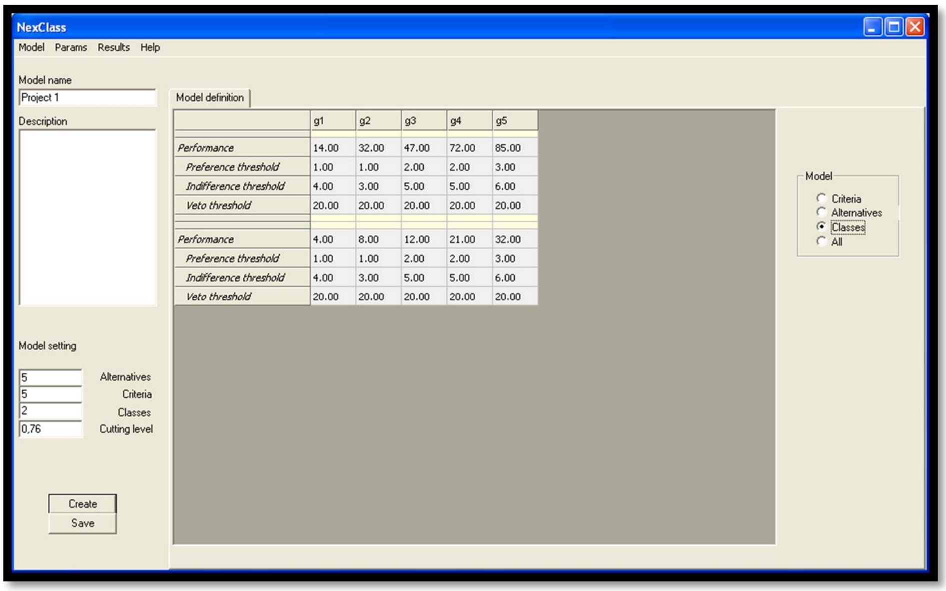

Figure 2: Categories Definition

Alternative definition: A subset of 6 target retailers was selected from the existing customer base, for training set. The selection was random not following any pattern. Their performance on the evaluation criteria was defined by the expert (Table 6) and set to the DSS (Figure 3).

	G1	G2	G3	G4	G5
a1	34.00	21.00	12.00	21.00	15.00
a2	42.00	34.00	27.00	57.00	43.00
a3	5.00	12.00	3.00	8.00	5.00
a4	13.00	6.00	22.00	8.00	10.00
a5	130.00	66.00	52.00	80.00	76.00
a6	1.00	6.00	5.00	8.00	7.00

Table 6: Alternatives' Performance to Evaluation Criteria

4.4.Solution and Results

Finally, the model was executed, and classification results were derived from NeXClass method. Results are depicted in Table 7, in comparison to classification of this set from expert using existing procedure. As it can be seen from this reference set, the model is in accordance with experts' opinion using existing procedure except one misclassification in C1.

Category	Nexclass	Existing Procedure
C1	{a1, a2, a5}	{a1, a2, a4, a5}
C2	{a3, a4, a6}	{a3, a6}

Table 7: Alternative Classification to Categories

The DSS provides classification of the results in a convenient way along with the various degrees calculated by the algorithm (Figures 4, 5).

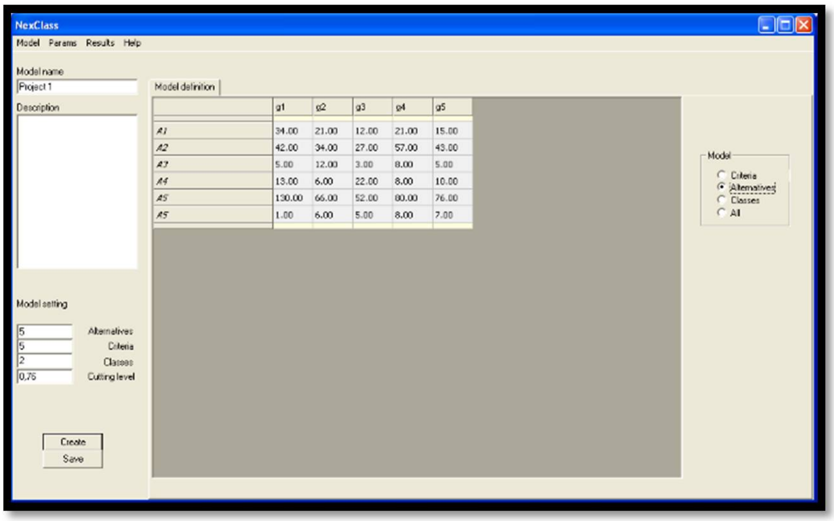

Figure 3: Alternatives Definition

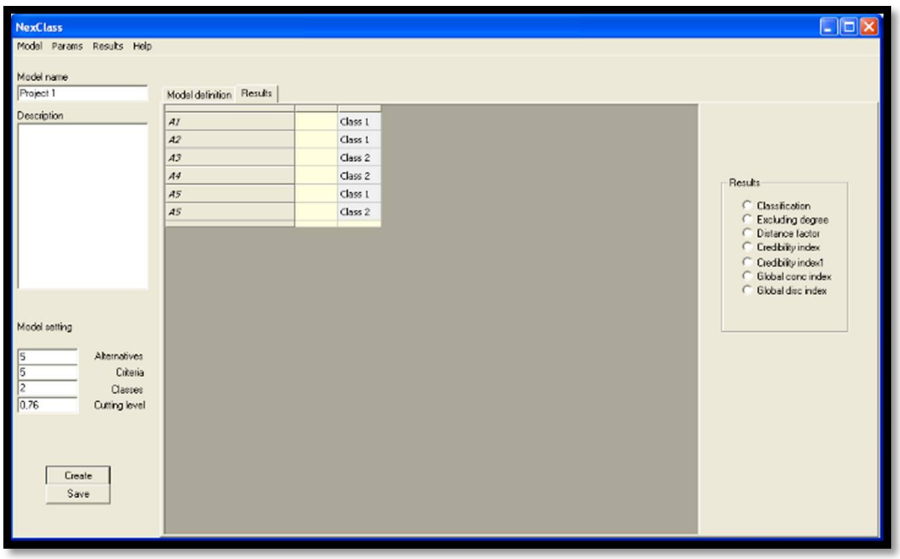

Figure 4: Classification Results

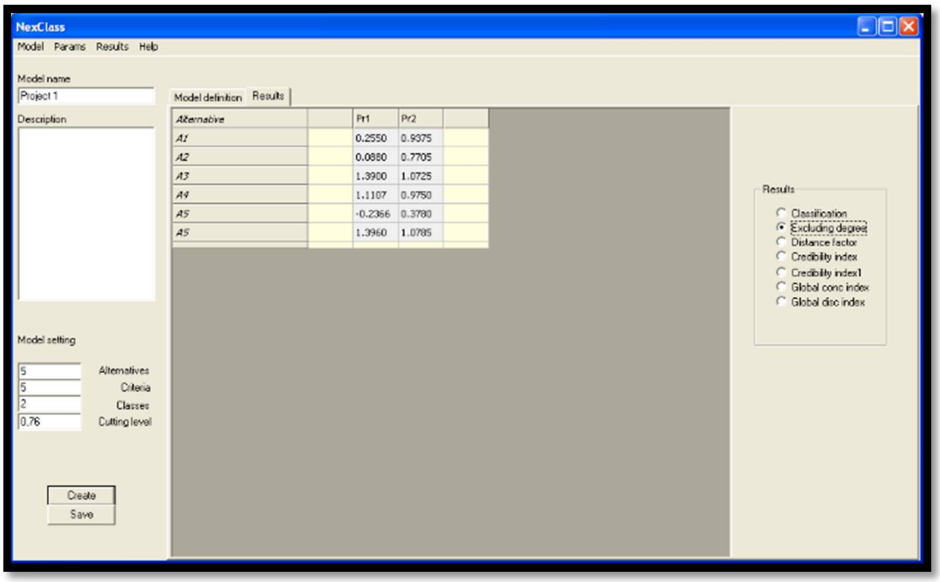

Figure 5: Excluding Degrees

5. Conclusion

In this paper we presented an algorithm for multi-criteria classification to ordered categories, as well as an extension to NeXClass DSS which implements the classification methodology. For illustration purposes, we presented a real world application of NeXClass DSS, within business setting. In collaboration with a marketing agency, we formulated a classification problem for retailer classification. Findings from DSS application and interaction with decision makers provide valid evidence that the methodology and DSS can provide sufficient support for classification problems. Its application reduces time to decision for large number of alternatives, and formulates the entire problem in a structured way, enhancing decision makers understanding, reducing thus misclassifications derived by existing heuristics. As a future enhancement, we plan to extract parameters from past decisions, in order to minimize decision maker's effort. From the above, we believe that both methodology and DSS can become a valuable tool for decision makers, in classification problems in a variety of domains.

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