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Ordinal Multicriteria Classification Algorithm for Investment Profiles Assessment

Georgios Rigopoulos [1,2]
[1]Department of Digital Innovation Management, Royal Holloway University of London, UK
[2]Department of Economics, University of Athens, Greece

Abstract— *NexClass is a Decision Support System which was introduced to support multicriteria classification of alternatives into predefined non-ordered categories. It was mainly used for decision support in financial domain and segmentation problems. This paper presents an extension of NexClass DSS to ordinal classification problems related to investment profiles. For each category a threshold is defined, which indicates its limit level with respect to the evaluation criteria. Then, assignment to classes is based on the concept of non-exclusivity, that defines at what degree a data tuple or alternative can be included into a specific category. Alternatives are assessed on the evaluation criteria, and non-excluding degrees are calculated for each class. Finally, an alternative is assigned to the class for which non-excluding degree gets the lowest value. The NexClass DSS implements the above classification algorithm, providing a user-friendly interface. In the paper we demonstrate the theory and the model as well as the DSS usage in a classification problem related to investment profiles.*

Keywords— *Multicriteria classification; decision support systems; NexClass.*

I. Introduction

Assignment of a set of actions (numbers, people, etc) to appropriate categories is a common objective in decision making problems at a variety of fields, including financial decisions, medical diagnosis, human resources management, marketing, pattern recognition and production management [1], [2], [3], [4], [5], [6], [7].

Classification can be divided in supervised which requires decision maker's contribution and refers to predefined categories and unsupervised which does not require decision maker's contribution and is executed automatically. We refer to supervised as sorting or classification depending on whether categories are ordered or not, while we refer to unsupervised as clustering. Multicriteria analysis offers a variety of methodologies and tools to solve sorting problems as well as choice and ranking ones [13], [14], [15], [16]. NeXClass is a nominal classification algorithm, implemented in a relevant decision support system. It is based on multicriteria analysis and solves classification problems to predefined non-ordered categories [8], [9], [10], [11], [12].

However, a variety of decision problems are related to ordinal classes. So, in this work we present an extension to NeXClass algorithm to support classification into ordered categories. The algorithm is based on outranking relations and the concept of category entrance threshold. In general, for each predefined category, a decision maker defines an entrance threshold, using available information. This threshold represents the minimum requirements for an alternative in terms of performance on the evaluation criteria in order to be included in this category. For each alternative, its performance against the criteria is compared with the entrance threshold of each 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 present the basic definition of NeXClass algorithm, as well as the classification methodology (Section 2). Next, the NeXClass DSS is presented, in terms of architecture and major functionalities (Section 3). Finally, in Section 4 a real world case study is presented in order to demonstrate the DSS usage in investment profile classification.

II. NeXClass Methodology

A. Overview

In order to support classification decisions in ordered predefined categories, we modify the NexClass classification algorithm. We use outranking relation principles as well as concordance and discordance indexes as follows:

- Given a set of alternatives, a set of predefined ordered categories and a set of evaluation criteria, the problem that we address is to classify an alternative into a specific category, with respect to alternative's performance to the evaluation criteria.
- We define the 'non-excluding principle', the basic rule for the classification of alternatives to categories as: *An alternative is assigned to a category, if it is 'not excluded' or 'roughly not excluded' according to the threshold entrance of this category*.
- In order to utilize the above 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 is it to be assigned into the category. In this case 'excluding degree' is minimized.
- The less the alternative performance overcomes the entrance threshold, the less likely is to be assigned into 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.

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In a classification problem, we follow an integrated methodology, which is separated in three main phases:

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

B. NexClass Algorithm

Key Notations :

$A = \{a_1, a_2, \ldots, a_m\}$: a set of alternatives for classification in a number of categories,

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

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

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

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

Excluding degree definition:

In order to estimate the validity degree 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 equivalently:

'Alternative $a \in A$ *is preferred or roughly preferred over the entrance threshold'*,

and estimate the validity degree 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 validity degree of the above statement we utilize outranking relations. An alternative is preferred over the entrance threshold if

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

Validity degrees of aSb_i^h and $b_i^h Sa$ 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 $b_i^h Sa$ 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 validity degree 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 $\gamma_i^{tot} = \frac{\gamma_i(b_i^h, a)}{1 + \gamma_i(a, b_i^h)}$ is based on outranking relations. Expressions $\gamma_i(a, b_i^h)$ and $\gamma_i(b_i^h, a)$ are the validity degrees 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 :

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

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

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

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

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

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

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

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 $\gamma_i^{tot}=\frac{\gamma(b_i^h,a)}{1+\gamma(a,b_i^h)}$ is calculated for every threshold for the category b_i^h and the fuzzy excluding degree is defined as

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

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 to categories:

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

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

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.

C. Classification Methodology

The application of the algorithm for classification problems comprises the following phases:

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

Next DM defines appropriate entrance thresholds for each category $\Omega=\{C^1,C^2,\dots,C^h\}$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. When 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.

III. NEXCLASS DECISION SUPORT SYSTEM

The algorithm is implemented in NeXClass DSS, a Decision Support System. The DSS was developed in C++ and is currently running under Windows OS. In this paper we present the updated version which supports the ordinal classification algorithm (fig. 1). The DSS provides the following main functionalities as modules.

- User management: Provides user authentication procedure options.
- Configuration: Provides general configuration options to customize the DSS interface, such as font selection, sizing, colour, and other interface parameters.
- Model import: Allows to import data from external source and formats the classification model.
- Model creation: Provides all the functionality to create a new model following the steps of the problem definition :phase of the methodology.
- Model reporting: Provides overview of the model, allowing editing to it.

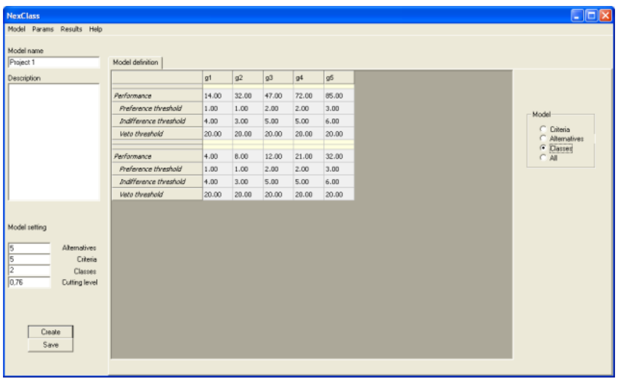

Figure 1. DSS screen

- Classification: Implements the classification algorithm, either on a training set or the set of the alternatives.

- Reporting: Presents 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.

IV. NeXClass Application to Classification of Investment Profiles

A. 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 classification of investment profiles for a targeted campaign related to a new product. Investment profiles evaluation of financial institution customers is an important decision problem for the campaign success and candidates have to be selected according to a number of carefully selected criteria.

Working in collaboration with a financial institution we developed a framework for customer aiming to support decision maker throughout the entire decision process. Since the desirable output of the decision process was the classification of customers to a number of predefined ordered groups according to specific criteria, NeXClass method was selected for the analysis and construction of the decision process. In brief, a number of semi-structured questionnaires were used to define the criteria and a number of categories were defined. 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 customer base and classification results were compared with classification deriving from the existing decision process.

B. Problem Definition

Following the steps of NeXClass methodology, a classification problem was formulated and the expert defined the required parameters reflecting decision preferences (Table 1). Two segments were identified, that represent the relevant market in terms of potential and profitability.

Segment 1 represents customers with low profitability and weak positions. This segment includes customers who perform low transaction volumes for more than 50% annually. The overall potential is relatively low and they are not profitable on a continuous basis.

Segment 2 represents customers with high profitability and strong positions. These perform high transaction volumes for more than 50% annually. The potential is quite strong and they are the most profitable of all.

TABLE 1. Segmentation Matrix

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

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

TABLE 2. Categories

	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

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 customer performance (Table 3).

TABLE 3. Criteria

	Definition	Scale
G1	Portfolio 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 transaction (in Euros)	1-100
G4	Average growth rate. Indicator showing increase in transaction ratio	1-100
G5	History and Potential factor. Based on statistical data	1-100

Criteria weights: Based on the above, the expert defined criteria weights (Table 3) and set the values to the DSS (Fig. 2).

TABLE 3. Criteria weights

	G1	G2	G3	G4	G5
Weights	20.00	15.00	45.00	10.00	10.00

Categories profiles

Next, the expert defined the limits of the categories setting appropriate values for each criterion in the scales defined previously. (Table 4) and set the values to the DSS (Fig. 2).

Table 4. Category profiles

	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

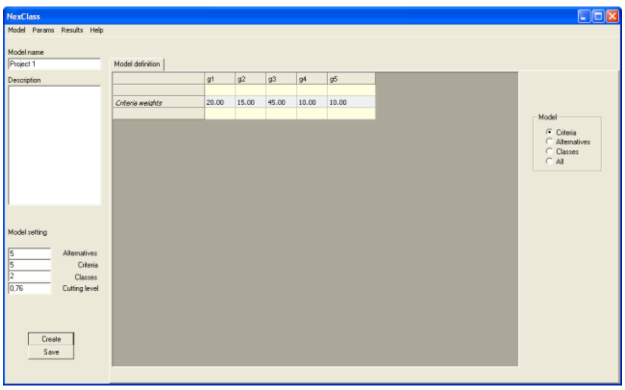

Figure 2. Criteria definition

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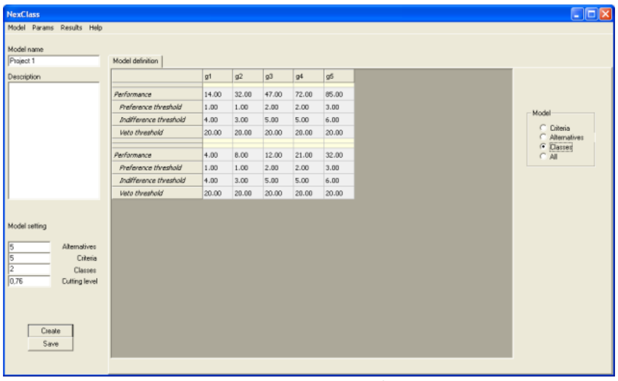

Figure 3. Categories definition

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 5) and set to the DSS (Fig. 3).

TABLE 5. Alternatives' performance to evaluation criteria

	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

4.3. *Solution and Results*

The model was executed, and classification results were derived using NeXClass algorithm. Results are depicted in Table 6, 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.

TABLE 6. Alternative classification to categories

Category	NeXClass	Existing procedure
C1	{a1, a2, a5}	{a1, a2, a4, a5}
C2	{a3, a4, a6}	{a3, a6}

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

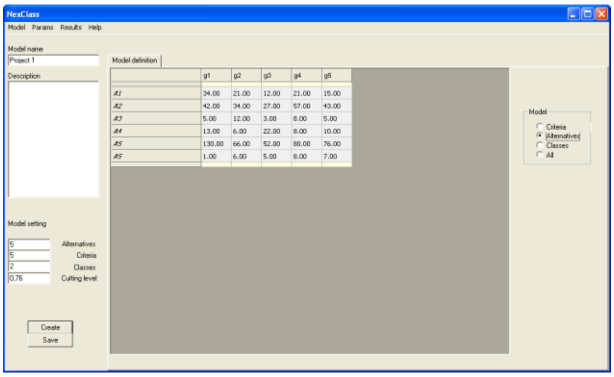

Figure 4. Alternatives definition

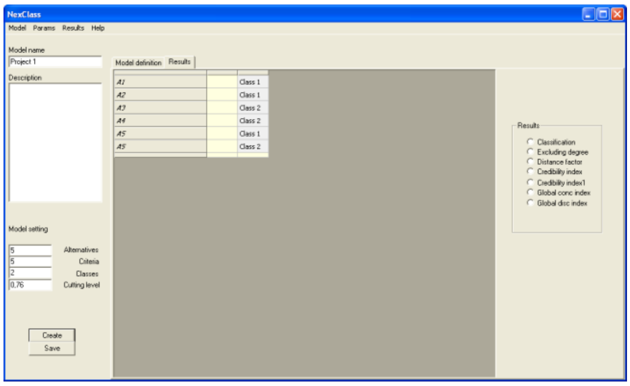

Figure 5. Classification results

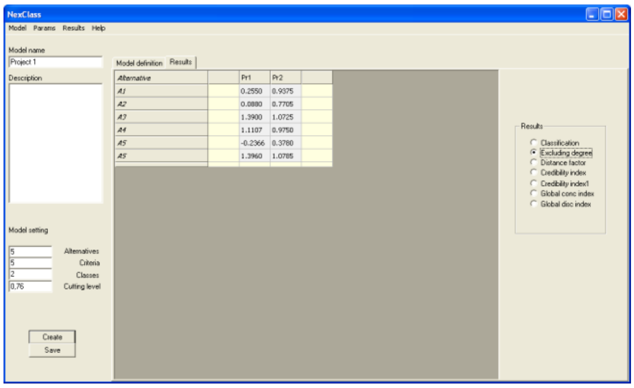

Figure 6. Excluding degrees

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