Chapter 30

Fuzzy Nominal Classification using Bipolar Analysis

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ABSTRACT

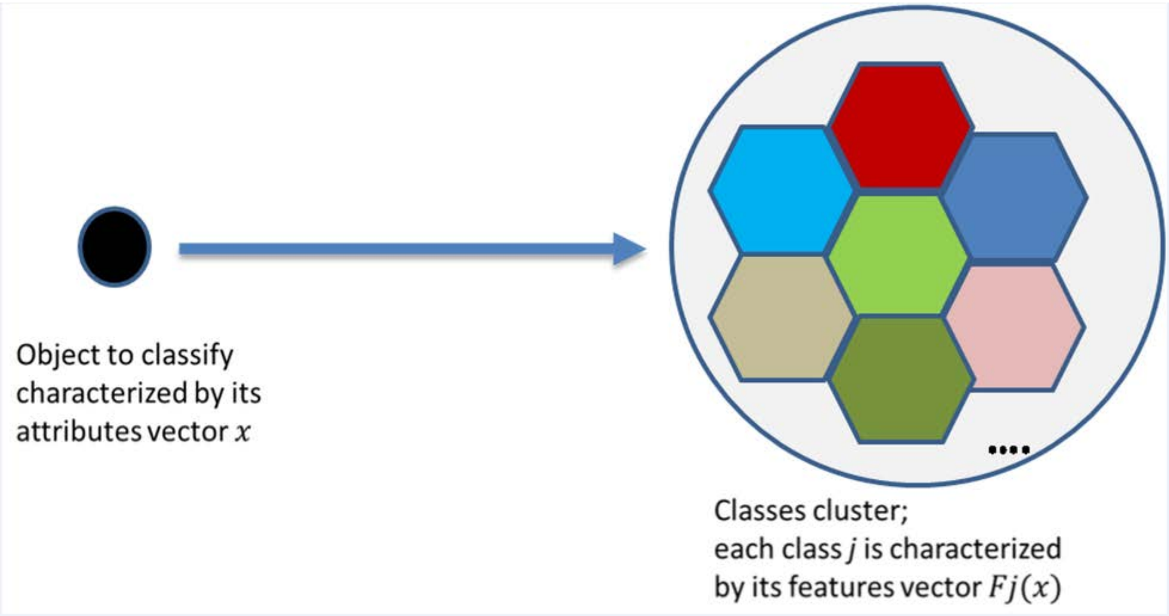
The process of assigning objects (candidates, projects, decisions, options, etc.) characterized by multiple attributes or criteria to predefined classes characterized by entrance conditions or constraints constitutes a subclass of multi-criteria decision making problems known as nominal or non ordered classification problems as opposed to ordinal classification. In practice, class entrance conditions are not perfectly defined; they are rather fuzzily defined so that classification procedures must be design up to some uncertainty degree (doubt, indecision, imprecision, etc.). The purpose of this chapter is to expose recent advances related to this issue with particular highlights on bipolar analysis that consists in considering for a couple of object and class, two measures: classifiability measure that measures to what extent the former object can be considered for inclusion in the later class and rejectability measure, a degree that measures the extent to which one should avoid including this object into that class rendering final choice flexible and robust as many classes may be qualified for inclusion of an object. This apparent theoretical subject finds applications in almost any socio-economic domain and particularly in digital marketing. An application to supply chain management, where a certain number of potential suppliers of a company are to be classified in a number of classes in order to apply the appropriate strategic treatment to them, will be considered for illustration purpose.

Keywords: Nominal Classification, Multi-Attributes, Multi-Features, Bipolar Analysis, Synergistic Aggregation, Weighted Cardinal Fuzzy Measure (WCFM), Choquet Integral.

INTRODUCTION

Many decision problems rising in different activities and domains such as social, economics, engineering, management, marketing, among others, concern the assignment or classification of objects according to their scores for a certain number of criteria or attributes to classes that are characterized by some features. These problems constitute, therefore, multi-criteria or multi-attributes (attributes of the object to classify) and multi-objectives (multi-features classes to choose) decision making problems. A unified framework is therefore needed to consider these problems because in the literature these two decision sub-problems have been almost always considered separately, see for instance references (Brans *et al*, 1984; Brans *et al*, 1986; Hurson and Zopounidis, 1997; Pomerol and Barba-Romero, 1993; Rigopoulos *et al*, 2008; Roy and Bouyssou, 1993; Saaty, 1980; Saaty, 2005; Steuer, 1986; Vincke, 1989) that consider these problems in different ways. Bipolar analysis that is being developed, see (Tchangani and Pérès, 2010; Tchangani, 2010; Tchangani *and al*, 2012), attempts to create this unified framework. The majority of contributions to classification problems encountered in the literature concern mainly the ordered classification case (that actually constitutes a relative evaluation process as objects to classify must be compared with regards to each other), objects must be ordered, let say, from most/least desired object to least/most desired one, see for instance (Doumpos and Zopounidis, 2002). Nominal classification process is illustrated by the following Figure 1, where one must choose from a cluster of classes where to include a given object.

Figure 1: illustration of nominal classification process



Formally the nominal classification problems considered in this chapter are defined by the following materials.

- An object *u* to be classified is characterized by a set of *m* attributes or criteria and the value (numeric or rendered numeric by a certain procedure) of attribute *l* is given by x_l so that this object can be designated by its attributes vector $x \in \Re_+^m$ (where $\Re_+^m$ represents the set of vectors of dimension *m* with non negative real entries); that is $x = [x_1 \quad x_2 \quad \ldots \quad x_m]^T$ where M^T stands for the transpose of vector or matrix M.
- The former defined object must be assigned to one of the *n* classes of the set $C = \{c_1, c_2, ..., c_n\}$; each class or category c_j is defined by n_j features, conditions, or constraints through scalar functions $f_j^k(x) \in \Re,\ k = 1, 2, ..., n_j$, of the attributes vector $x \in \Re_+^m$; a feature is a mapping from attributes evaluation space $\Re_+^m$ onto the real number set $\Re$. A class is therefore completely determined by its features vector $F_j(x) = \left[f_j^1(x) \quad f_j^2(x) \quad \ldots \quad f_j^{n_j}(x)\right]^T$.

One should notice that without loss of generality we consider that attributes are positively evaluated; indeed in practice (and mainly in digital marketing application) one can obtain this situation using some transformations. Furthermore, in practice it is rather rare that features $f_j^k(x) \in \Re,\ k = 1, 2, ..., n_j$ of classes be determined exactly. Most of the time they will be described only up to some degree of uncertainty with linguistic characterization such as high, low, mean, approximatively, near to, etc. that is they will be described fuzzily leading to what we name fuzzy nominal classification.

The purpose of nominal classification methods or algorithms is then to establish a procedure that select the most appropriate class where to include the considered object; one may notice that this is an absolute decision making process as objects to classify are not compared with each other.

Nominal classification finds applications in almost any socio-economic domain. Here is some applications of major socio-economic domains briefly presented; in the next section the particular domain of digital marketing or e-commerce will be considered.

Finance and banking

In finance and banking for instance, decision maker(s) face the problem of classifying customers seeking a credit or a service into classes defined by entrance thresholds with regard to their performance in some attributes (age, annual revenue, profession category, etc.) for instance or for professionals which service the bank should proposes them (Rigopoulos *and al*, 2008; Tchangani, 2009).

International commerce

In international finance or commerce, countries are often classified in different categories in terms of risk to which potential investors will be exposed in these countries (country risk classification) by using a certain number of attributes such as GDP per unit of energy use, telephone mainlines per 1000 people, human development index (HDI), percentage of military expenditure of the central government expenditure and others, see (Wang, 2004).

Medical domain

This is probably the most indicated domain for nominal classification. Indeed, in medical domain, a medical practitioner classifies for instance a patient as suffering a fever if its temperature is beyond a threshold and/or if it presents some other symptoms.

Human resources management

When selecting a candidate for a given job, human resources managers must ensure that this candidate have some attributes that are in adequacy with the job (Pomerol and Barba-Romero, 1993); this is a nominal classification problem that is one must responds to the question, do the attributes of this candidate permit to classify him/her in acceptable class or rejected class.

Academic

In academic, a student will get his/her diploma or degree if his/her marks in some different disciplines are beyond some thresholds. In the same way for admission process, students may be classified as definitely admitted, definitely rejected, or possibly admissible.

Engineering and design

Constraints satisfaction in artificial intelligence and operations research, is the process of finding a solution to a set of constraints. For instance, the design of an infrastructure (a bridge, a building, etc.) must be able to support a certain load and in the same way necessitate less materials.

One can imagine many other applications in different socio-economic domains that fall under fuzzy nominal classification procedure.

DIGITAL MARKETING AND NOMINAL CLASSIFICATION

In everyday business life, many examples can be found where fuzzy nominal classification approach would be useful. In the customer relationship management for instance, a standard classification would sharply classify customers of a company into a certain segment depending on their buying power, age and other attributes. If the client's potential of development is taken into account, the clients often cannot be classified into only one segment anymore, i.e. customer equity. Other application domains may concern portfolio analysis, credit worthiness, marketing theory and some personalization issues.
Having fuzzy classes opens new perspectives for positioning the customers inside the classification space. In contrast to a sharp classification where the only available information is a class belonging, a fuzzy classification can derive the precise position of the customers inside the classes based on their membership degrees. This important information offers new possibilities for segmenting, targeting and controlling customers.

Segmentation

Segmentation consists in dividing a certain market into many classes known as segments with the main objective to personalize an advertising message. More focus has been placed on segmentation within digital marketing, in order to target specific markets in both business to business and business to consumer sectors. Therefore, segmentation is typically a nominal classification problem where a potential market is segmented into several classes for appropriate treatment (appropriate advertising campaign for instance). In terms of digital marketing, segmentation can be viewed as presenting the appropriate items to appropriate customer. When a potential customer connect to a given online provider website, he/she can specify his preference for products of his/her choice; these preference measures that constitute his/her attributes can be used to classify him into an appropriate class for appropriate treatment purpose.

Influencer marketing

With the expansion of social networks, it is possible for online advertiser to do a sort of indirect advertising by targeting some leaders (users with a great number of followers) identified as important nodes within communities, known as influencers or leaders. This is becoming an important concept in digital targeting. It is possible to reach influencers via paid advertising, such as Facebook or Google campaigns, or through sophisticated CRM (social customer relationship management) software, such as Microsoft Dynamics and Sales force CRM. Many universities now focus, at Masters level, on engagement strategies for influencers. The leader may be seen as a representative of a certain class, so given a potential customer he/she will be included in the class of leader with whom he/she is more closed in the attributes space.

Recommender systems

Nowadays, many customers purchase their products on internet and online providers such as Amazon, eBay, PriceMinister, etc. offer possibilities for customer to specify his/her preferences that can be considered in terms of nominal classification as its class feature and then the recommender system of the provider will determine potential items (characterized by their contains that can be considered as their attributes) that can be recommended to that customer.

Here again, there are many imaginable problems of digital marketing that can be formulated as fuzzy nominal classification problems which can be efficiently solved by approach being presented in this chapter.

BIPOLAR APPROACH FOR FUZZY NOMINAL CLASSIFICATION

A number of multicriteria decision aid (MCDA) methods have been developed for nominal classification. They include multicriteria filtering (Perny, 1998), a method based on concordance and non-discordance principles; PROAFTN, see (Belacel, 2000), a multicriteria fuzzy classification method; a method based on fuzzy integrals, see for instance (Guzman, 2003); TRINOMFC method (Leger and Martel, 2002) that computes local concordance; or the stochastic multicriteria acceptability analysis (SMAA) method that supports incomplete or inaccurate preference, see (Yevseyeva, 2007).

If these methods have been successfully applied in practice, many of them do have usability limitation (with regard to final users) such as complexity of how parameters must be specified by the users. The intention of this chapter is to add a method to the panorama of existing methods that we hope will be easier (because of its flexibility) to use by the final users who in general are non specialists. In this chapter we consider a method of nominal classification that is based, for a given object and a given class, on two measures corresponding respectively to what extent the object can be included in the class and to what extent it should be excluded, similar to satisficing games theory approach, see (Stirling, 2003).

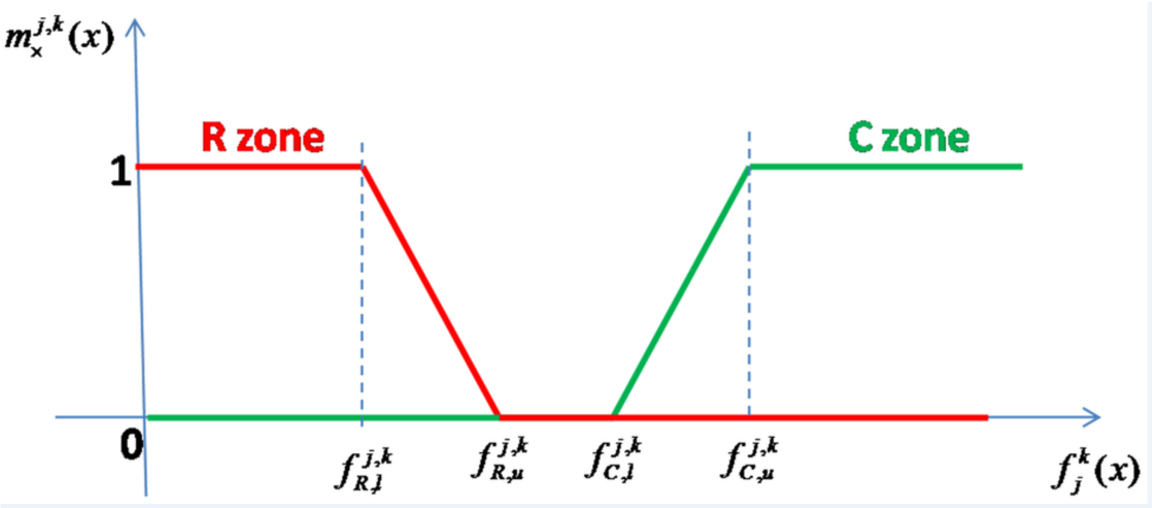
Bipolarity is pervasive in human decision process in general and classification process in particular; this bipolarity results often in uncertainty in decision making processes. For instance a medical doctor who receives a patient with a certain level of body temperature must decide if the patient is suffering of a fever or not; in general doctor may know with certainty the category of the patient if the temperature range in a certain interval and will be less certain for other range of temperature. The recommender system, segmentation process, or leader marketing approach, in digital marketing can be considered in the same way.

Bipolar reasoning is pervasive in decision analysis and constitutes a sort of divide to better apprehend paradigm. The stepping stones in bipolar analysis approach, for nominal classification, are the classifiability and rejectability measures $\mu_C^j(u)$ and $\mu_R^j(u)$ given a class c_j and an object u; so their derivation is an important step towards a sound classification algorithm. These measures must be established considering the performance of the considered object with regard to the considered class. As mentioned above, each feature *k* characterizing a class c_j is fuzzily described; as the characterization functions of features are scalar (or rendered scalar), this fuzzy description consists generally in four types. Thus, to consider that the object *u* characterized by vector *x* belongs to the class c_j if one were to decide only based on feature *k*, we consider the range of $f_j^k(x)$ to be partitioned into two labels or zones: rejection zone (**R zone**), that is if $f_j^k(x)$ belongs to this zone one should categorically exclude including object *u* in the corresponding class and classification zone (**C zone**) where if $f_j^k(x)$ lays in, one should consider including the object *u* in this class; finally there is a zone where decision of including or excluding is not obvious that we refer to as doubtful zone. Let use define by $m_C^{j,k}(x)$ and $m_R^{j,k}(x)$the membership degrees of these zones respectively. The membership function $m_\times^{j,k}(x)$ where × stands for *R* or *C* is a degree that measure the extent to which one should reject or consider classifying object *u* in the class c_j; given an object *u* and its attribute vector x, these membership functions depends on the value of $f_j^k(x)$; four main typologies characterize the behavior of $f_j^k(x)$ that conditions the classification of object u in the class c_j.

- Higher is better feature for classification; in this case to determine classifiability and rejectability membership functions, four values must be specified for feature $f_j^k(x)$; namely

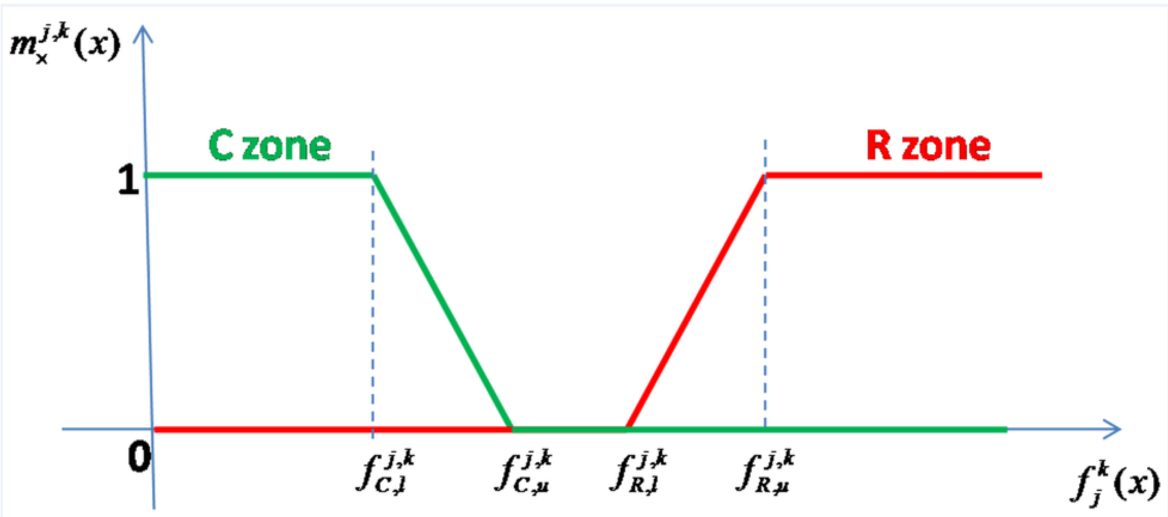
$f_{R,l}^{j,k}$ (value below which, one should definitely discarded class c_j based on feature $f_j^k(x)$), $f_{R,u}^{j,k}$ (value above which, one cannot exclude class c_j), $f_{C,l}^{j,k}$ (value below which one cannot consider class c_j for inclusion of object u), and $f_{C,l}^{j,k}$ (value above which, one should definitely include object u in class c^j based on feature $f_j^k(x)$). The memberships functions $m_R^{j,k}(x)$ and $m_C^{j,k}(x)$ are therefore given by the following Figure 2.

Figure 2: membership functions for high is better feature



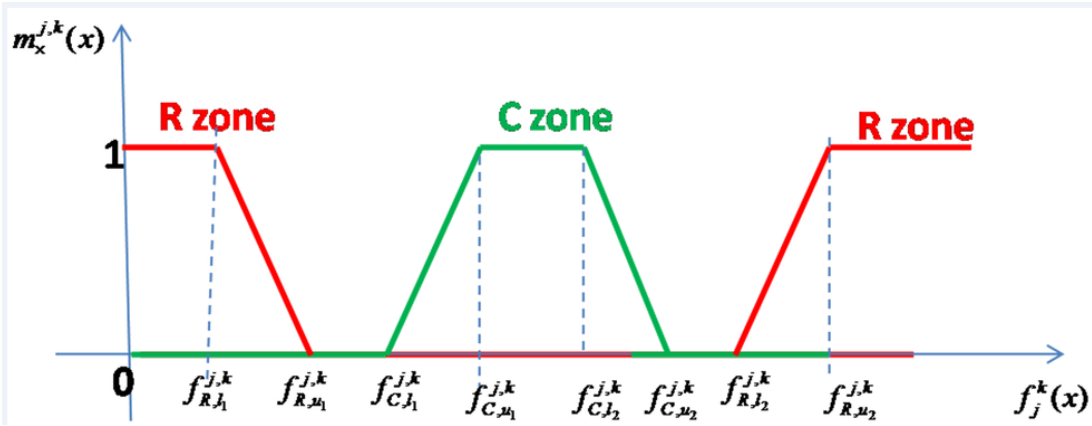
- Low is better feature, this case is the contrary of the above one so that the membership functions of R zone and C zone, $m_R^{j,k}(x)$ and $m_C^{j,k}(x)$ are given by the Figure 3 below.

Figure 3: membership functions for low is better feature



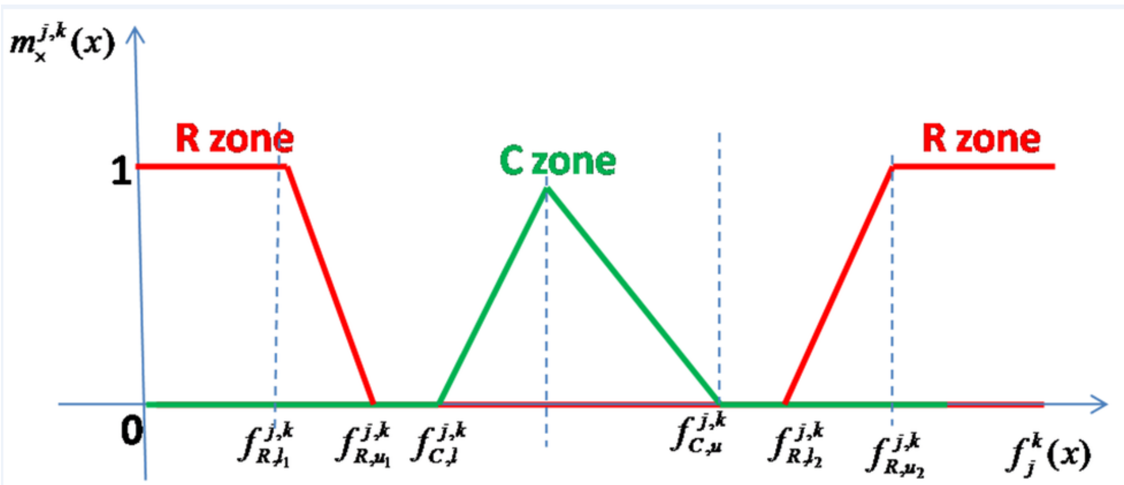
- Range valued feature, to consider including the object *u* in the class c_j using only the feature *k*, $f_j^k(x)$ must belong to an interval; in this case the R zone and C zone membership functions are given by the following Figure 4.

Figure 4: membership functions for range value feature



- A targeted or single value feature, to consider including the object *u* in the class c_j using only the feature *k*, $m_R^{j,k}(x)$ and $m_C^{j,k}(x)$ are given as depicted on following Figure 5.

Figure 5: membership functions for targeted value feature



Remark: It is worth noticing that the doubtful zone may constitute an overlapping zone of C zone and R zone; that is in terms of parameters defining membership functions of these zones, one may have $f_{C,l}^{j,k} \leq f_{R,l}^{j,k}$ on Figure 2; $f_{R,l}^{j,k} \leq f_{C,u}^{j,k}$ on Figure 3; $f_{C,l_1}^{j,k} \leq f_{R,u_1}^{j,k}$ and $f_{R,l_2}^{j,k} \leq f_{C,u_2}^{j,k}$ on Figure 4; and finally $f_{C,l}^{j,k} \le f_{R,u_1}^{j,k}$ and $f_{R,l_2}^{j,k} \le f_{C,u}^{j,k}$ on Figure 5. Furthermore, membership functions shapes are just indicative; any shapes in similar forms are admissible.

AGGREGATION PROCEDURE

As there are many features characterizing each class, their membership functions must be aggregated to derive a global classifiability and rejectability measures. A sound and useful aggregation operator is therefore needed. Given the synergy obtained by considering separately, classifiability and rejectability zone, it is obvious of considering a synergistic aggregation operator. Furthermore, features characterizing classes do not necessarily have the same importance in the classification process and experts may be able to weight them in terms of normalized vector ω. In this case, Choquet integral associated with a weighted cardinal fuzzy measure (wcfm), see Tchangani (2013), is a suitable aggregation operator.

Many aggregation procedures do exist in literature, going from the basic arithmetic mean to more sophisticated ones that take into account the interaction nature of elements to aggregate, see Grabisch (1996). One such sophisticated operator that take into account interaction behavior such as synergy, redundancy or independency between elements to aggregate is the so called Choquet integral (Grabisch, 1996) which utilization in practice is sometime compromised by the difficulty to define a tractable associated capacity or fuzzy measure. Let $X = \{x_1, x_2, ..., x_n\}$ be a set of numerically valued elements to aggregate by Choquet integral, the following definition gives the necessary materials for this purpose.

Definition 4. *Let 2^X be the power set of X, a function $\mu : 2^X \to [0,\ 1]$ is a capacity or a fuzzy measure over X if it verifies:*

i) $\mu(\varnothing) = 0$

ii) $\mu(X) = 1$

iii) $\mu(A) \le \mu(B), \quad \forall\ A \subseteq B \subseteq X$

The Choquet integral of vector x of elements of the set X associated to the capacity or fuzzy measure μ is given by equation (1)

$$C_\mu(x) = \sum_{i=1}^{n} \left(x_{\sigma(i)} - x_{\sigma(i-1)}\right) \mu(A_i) \qquad (1)$$

where σ is a permutation over the set X verifying relations of equation (2)

$$x_{\sigma(1)} \le x_{\sigma(2)} \le ... \le x_{\sigma(n)} \quad with \quad x_{\sigma(0)} = 0 \qquad (2)$$

and the subset $A_i \subseteq X$ is given by equation (3)

$$A_i = \{\sigma(i), \sigma(2), ..., \sigma(n)\} \qquad (3)$$

The difficulty of computing Choquet integral is to define a fuzzy measure over the set *D* that necessitates obtaining $2^{|X|} - 2$ coefficients that represent the measure of subsets of *X* other than $\emptyset$ and *X* ; $|X|$ stands for cardinal of *X* (the number of elements of *X*). In the case where elements to aggregate behave in synergy as it is the case here because of the bipolarity, and if it is possible to rank these elements by assigning them relative importance normalized weights, one can use a weighted cardinal fuzzy measure (WCFM) that leads to a straightforward formula for the corresponding Choquet integral.

Definition 5. *A weighted cardinal fuzzy measure (WCFM) over X associated to a relative normalized weights vector* $\omega = \left[\omega_1 \quad \omega_2 \quad \ldots \quad \omega_n\right]$ *is given by equation (4)*

$$\mu(\Omega) = \frac{|\Omega|}{X}\left(\sum_{j\in\Omega}\omega_j\right) \tag{4}$$

where Ω *is a subset of X.*

It is straightforward to verify that this function fulfils conditions of a capacity or fuzzy measure.

Let us denote by $C_{\omega}^{wcfm}(x)$ the Choquet integral of numerical *n* dimension vector *x* associated to a WCFM with relative vector ω, then this integral, is given by equation (5)

$$C_{\omega}^{wcfm}(x) = \sum_{k=1}^{n}\left\{\left\{\left(\frac{n-(k-1)}{n}\right)\left(\sum_{j\in A_k}\omega_k\right)\right\}\left(x_{\sigma(k)} - x_{\sigma(k-1)}\right)\right\} \tag{5}$$

where A_k is defined as in the equation (3). There is no difficulty to verify this straightforward formula.

Aggregated classifiability and rejectability measures

Given an object *u* and a class c_j, the overall classifiability degree $\Psi_C^j(u)$ and the overall rejectability degree $\Psi_R^j(u)$ of the class c_j are obtained by aggregating the memberships degrees $m_C^{j,k}(x)$ and $m_R^{j,k}(x)$; let us denote by $m_C^j(x)$ and $m_R^j(x)$, n_j dimension vectors of classifiability and rejectability degrees for class c_j; $\Psi_C^j(u)$ and $\Psi_R^j(u)$ are obtained as Choquet integral of vectors $m_C^j(x)$ and $m_R^j(x)$ associated with weighted cardinal fuzzy measure determined by normalized weight vector ω_j as given by following equation (6)

$$\Psi_C^j(u) = C_{\omega_j}^{wcfm}\left(m_C^j(x)\right) \quad \textit{and} \quad \Psi_R^j(u) = C_{\omega_j}^{wcfm}\left(m_R^j(x)\right) \tag{6}$$

Final normalized classifiability and rejectability measures, namely $\mu_C^j(u)$ and $\mu_R^j(u)$ are given by the following equation (7)

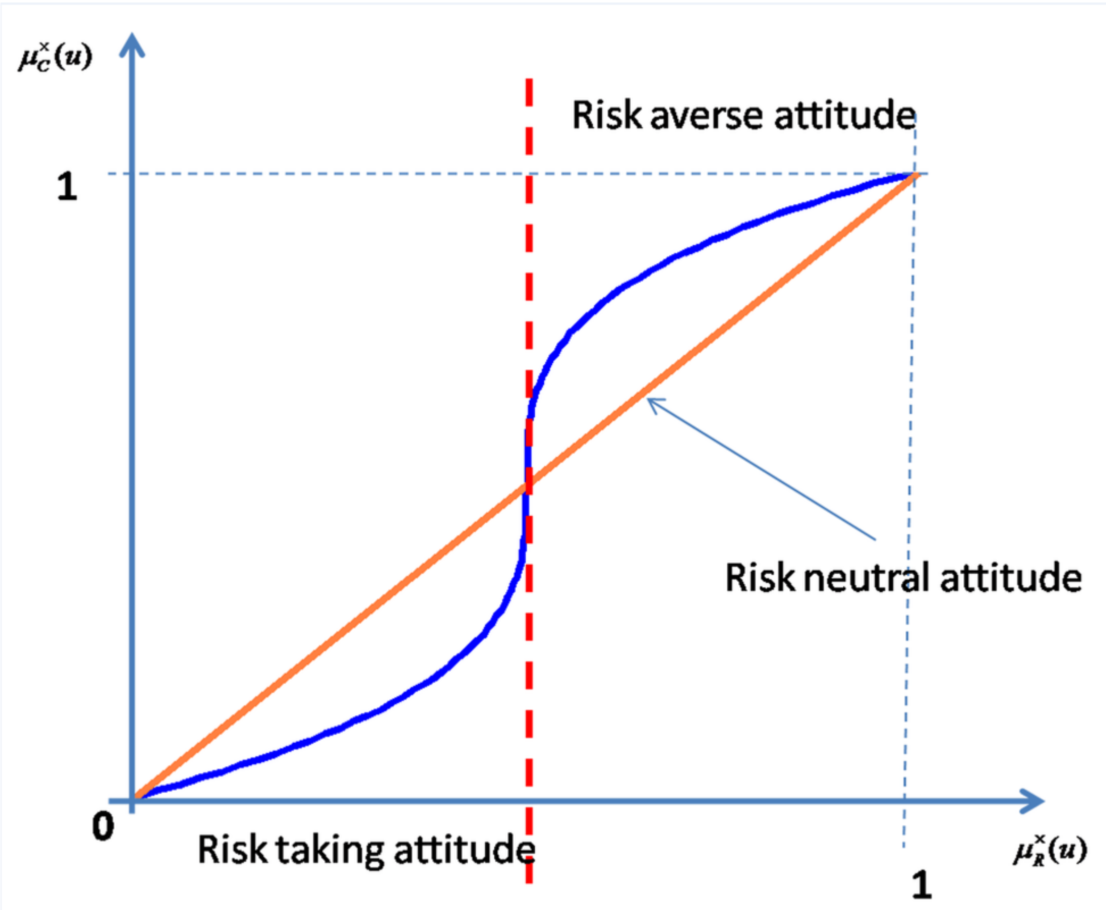
$$\mu_C^j(u) = \frac{\Psi_C^j(u)}{\sum_{k=1}^{n}\Psi_C^k(u)} \quad \textit{and} \quad \mu_R^j(u) = \frac{\Psi_R^j(u)}{\sum_{k=1}^{n}\Psi_R^k(u)} \tag{7}$$

For each object *u*, one can define a set of classes in which it can potentially to be included up to a certain risk level through caution (or risk averse) or boldness (or risk taking) function *q*; the classifying set $C_q(u)$ for object *u* with regards to boldness function *q* is given by the following equation (8)

$$C_q(u)=\left\{c_j : \mu_C^j(u)\geq q\left(\mu_R^j(u)\right)\right\} \tag{8}$$

where q is a non decreasing function on unit interval $[0, \quad 1]$. This function q can be used as a parameter to manage risk averse attitude of decision makers. It is well known that, see (Tversky and Kahneman, 1974), decision makers may exhibit risk taking attitude for low negative impact that is here low rejectability measure and risk averse for high negative impact that is high rejectability measure. Following Figure 6 shows possible shapes for function q. In many cases this function can just be a linear function that is $q\left(\mu_R^j(u)\right)=q\mu_R^j(u)$ where q is a constant that is used to manage the size of classifying set; $q = 1$ corresponds to risk neutral attitude.

Figure 6: shapes of classifying function taking into account risk attitude



The ultimate class $c^*(u)$ where to include actual object u may be chosen to optimize a certain index; here is two possible indices:

Maximum ratio: $c^*(u)$ is given in this case by following equation (9) below

$$c^*(u)=\max_{c^j\in C_q(u)}\left\{\frac{\mu_C^j(u)}{\mu_R^j(u)}\right\} \tag{9}$$

Maximum difference: $c^*(u)$ is obtained by maximizing the difference between classifiability measure and the corresponding boldness function of rejectability measure as shown by following equation (10)

$$c*(u) = \frac{\max}{c_j \in C_q(u)} \left\{ \mu_C^j(u) - q\left(\mu_R^j(u)\right) \right\} \tag{10}$$

APPLICATION

This application is adapted from data of a problem considered by (Araz and Ozkarahan, 2007) and cited in (Nemery de Bellevaux, 2009). A manufacture company, in the field of electronic industry, would like to develop strategic partnerships with a set of (hopefully) innovative suppliers. Integration of the right suppliers in concurrent engineering teams is an important factor for success, see (Araz and Ozkarahan, 2007), For this purpose, the company would like to evaluate its suppliers (and some emergent ones) in order to distinguish them. The purpose is obviously not to rank the suppliers. A ranking of the suppliers may not be adapted since for example the worst supplier may be completely in line with the need of the company. On the other hand, the best supplier may not be adapted at all for the company. In this situation, new suppliers need to be find. For these reasons the company wants to compare the suppliers according to some norms or reference profiles which will be representative of their strategy and needs; that is nominally classifying potential suppliers into predefined classes or categories. Therefore, classes and attributes characterizing suppliers are discussed in the following.

Classes or categories

Therefore, the company defines 4 classes or categories described as:

- c_1: suppliers for strategic partnerships
- c_2: promising suppliers that must be supported via supplier development programs
- c_3: suppliers for competitive partnerships: they have to be considered for competitive partnerships for some products
- c_4: suppliers to be pruned: they should no longer be considered for the partnership in any level

Attributes or criteria

The company uses 10 attributes described below to evaluate potential suppliers:

- a_1: Support in Product Structural Design
- a_2: Support in Process Design and Engineering
- a_3: Design Revision time
- a_4: Prototyping time
- a_5: Level of Technology
- a_6: Quality Performance
- a_7: Financial Strength
- a_8: Cost Reduction Performance
- a_9: Delivery Performance
- a_{10}: Ease of communication

All attributes, except of a_3 and a_4 (small is better), have to be maximized (high is better) and the preference parameters are given in Table 1. The values of the parameters are determined by the interaction with the concurrent design team.

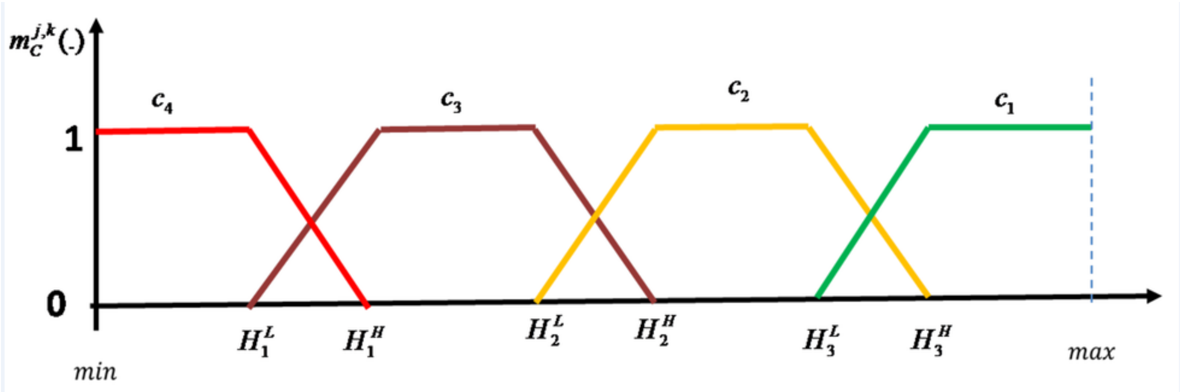
Table 1: data of the considered application

u_i	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
u_{01}	84	83	12	7	85	85	80	85	95	90
u_{02}	72	78	7	5	70	70	80	75	95	90
u_{03}	70	82	7	7	80	85	89	65	90	95
u_{04}	70	68	20	25	75	70	60	90	70	90
u_{05}	70	95	15	5	95	50	95	95	80	95
u_{06}	90	85	30	32	85	60	70	77	80	85
u_{07}	80	75	15	7	80	95	70	84	90	80
u_{08}	86	90	10	5	85	85	92	75	99	90
u_{09}	92	85	30	26	90	60	92	75	90	90
u_{10}	70	65	25	28	60	60	75	70	60	60
u_{11}	75	85	30	32	65	50	90	80	89	60
u_{12}	92	90	8	5	90	90	85	92	99	90
u_{13}	72	75	27	10	80	70	80	70	89	80
u_{14}	55	60	28	32	70	85	60	65	70	60
u_{15}	95	90	8	5	90	90	85	85	98	90
u_{16}	95	95	8	7	95	95	95	92	95	90
u_{17}	70	75	24	12	85	80	84	70	86	80
u_{18}	80	70	10	7	85	60	80	60	95	90
u_{19}	95	90	7	7	95	85	85	95	97	95
u_{20}	60	70	30	30	60	60	80	70	60	80
u_{21}	90	90	15	5	80	90	80	75	99	90
u_{22}	70	60	30	15	60	50	60	75	70	65
Weights	0.15	0.1	0.1	0.1	0.08	0.15	0.05	0.12	0.1	0.05

Results

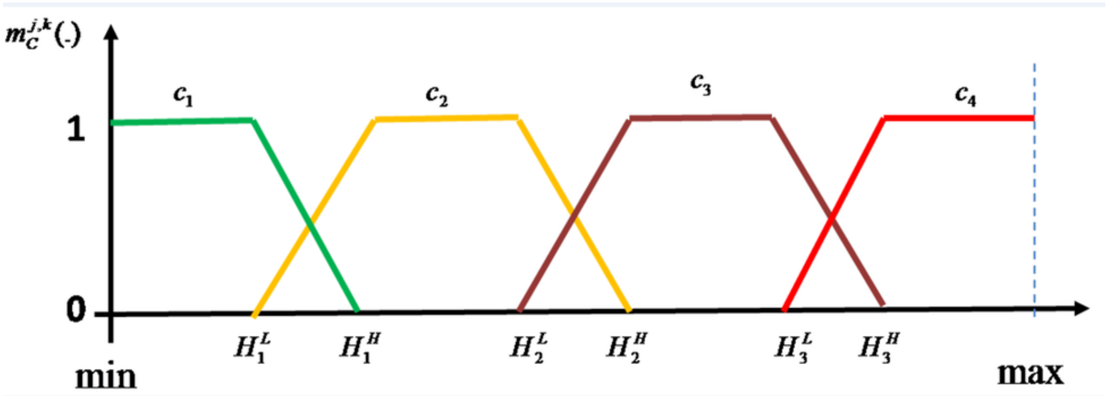
In this application features characterizing classes correspond to attributes of the object to classify so that C zone (C zone) and R zone are determined with regards to attributes values range. Classifiability zone of each class for high is better attributes that is criteria a_1, a_2 and a_5 to a_{10} is depicted on the following Figure 7

Figure 7: classifiability zone of high is better attributes (a_1, a_2 and a_5 to a_{10})



and that for criteria a_3 and a_4 is given by Figure 8.

Figure 8: classifiability zone of low is better attributes (a_3 and a_4)



Parameters H_1^L, H_1^H, H_2^L, H_2^H, H_3^L, H_3^H, shown on Figures 7 & 8, are obtained as

$$\begin{aligned} H_1^L &= (\min + h) - \delta h, \quad H_1^H = (\min + h) + \delta h \\ H_2^L &= (\min + 2h) - \delta h, \quad H_2^H = (\min + 2h) + \delta h \\ H_3^L &= (\min + 3h) - \delta h, \quad H_3^H = (\min + 3h) + \delta h \end{aligned}$$

where $h = \dfrac{\max - \min}{4}$ and δ represent a certain percentage of h, here we choose $\delta = 10\%$ meaning that the overlapping zone between two consecutive classes correspond to 20% of h. For sake of simplicity we consider that C zone and R zone for each attribute constitute a fuzzy discretization of the values range of that attribute, that is we have $m_R^{j,k}(.) = 1 - m_C^{j,k}(.)$.

Values of parameters H_1^L, H_1^H, H_2^L, H_2^H, H_3^L, H_3^H are given on the following Table 2.

Table 2: classifiability zone parameters

	a_1	**a_2**	**a_3**	**a_4**	**a_5**	**a_6**	**a_7**	**a_8**	**a_9**	**a_{10}**
min	55	60	7	5	60	50	60	60	60	60
max	95	95	30	32	95	95	95	95	99	95
H_1^L	64	67.88	12.2	11.10	67.88	60.13	67.88	67.88	68.78	67.88
H_1^H	66	69.63	13.33	12.43	69.63	62.38	69.63	69.63	70.73	69.63
H_2^L	74	76.63	17.93	17.82	76.93	71.38	76.93	76.93	78.53	76.93
H_2^H	76	78.38	19.08	19.18	78.38	73.63	78.38	78.38	80.48	78.38
H_3^L	84	85.38	23.68	24.58	85.38	82.63	85.38	85.38	88.28	85.38
H_3^H	86	87.13	24.83	25.93	87.13	84.88	87.13	87.13	90.23	87.13

Using data of Table 1 and these parameters of Table 2, we obtain classifiability and rejectability measures given by the following Table 3.

Table 3: classifiability and rejectability measures of each supplier with regard to each class

	Classifiability measure, $\mu_C^j(u)$				Rejectability measure, $\mu_R^j(u)$			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
u_{01}	0.5000	0.5000	0.0000	0.0000	0.1000	0.1000	0.4000	0.4000
u_{02}	0.3626	0.0638	0.5735	0.0000	0.1634	0.3007	0.1167	0.4191
u_{03}	0.8226	0.1075	0.0388	0.0311	0.0800	0.2675	0.3206	0.3319
u_{04}	0.0768	0.0000	0.7754	0.1478	0.2718	0.4094	0.0762	0.2425
u_{05}	0.8082	0.0881	0.0634	0.0404	0.0843	0.2874	0.3057	0.3226
u_{06}	0.0507	0.4617	0.1326	0.3549	0.3332	0.1778	0.2908	0.1982
u_{07}	0.2521	0.6713	0.0767	0.0000	0.1973	0.1002	0.2844	0.4182
u_{08}	0.9697	0.0121	0.0182	0.0000	0.0150	0.3113	0.2977	0.3759
u_{09}	0.6116	0.0401	0.0357	0.3126	0.1278	0.3384	0.3391	0.1948
u_{10}	0.0000	0.0000	0.1678	0.8322	0.3888	0.3888	0.1851	0.0373
u_{11}	0.0372	0.3191	0.0195	0.6242	0.3313	0.1896	0.3701	0.1090
u_{12}	0.9942	0.0058	0.0000	0.0000	0.0017	0.2990	0.3497	0.3497
u_{13}	0.0642	0.2744	0.6311	0.0303	0.3206	0.2081	0.1236	0.3477
u_{14}	0.0266	0.0000	0.0454	0.9281	0.2983	0.3900	0.2808	0.0309
u_{15}	0.9513	0.0487	0.0000	0.0000	0.0126	0.2461	0.3706	0.3706
u_{16}	1.0000	0.0000	0.0000	0.0000	0.0000	0.3333	0.3333	0.3333
u_{17}	0.0069	0.6238	0.3631	0.0062	0.3825	0.0889	0.1435	0.3850
u_{18}	0.4861	0.2917	0.0347	0.1875	0.1705	0.2203	0.3540	0.2552
u_{19}	0.9942	0.0058	0.0000	0.0000	0.0017	0.2990	0.3497	0.3497
u_{20}	0.0000	0.0424	0.0932	0.8644	0.4045	0.2913	0.2524	0.0518
u_{21}	0.8280	0.1465	0.0255	0.0000	0.0567	0.2181	0.3205	0.4047
u_{22}	0.0000	0.0216	0.1937	0.7847	0.4059	0.3288	0.2006	0.0647

In the case of risk neutral attitude, that is the classifying function is given by $\mu_C^j(u) = \mu_R^j(u)$, we obtain classifying set *C(u)* and the ultimate inclusion class $c^*(u)$, obtained by the maximum ratio criterion that is $c^*(u) = \max_{c_j \in C_q(u)} \left\{ \frac{\mu_C^j(u)}{\mu_R^j(u)} \right\}$, for each alternative *u* as given by the following Table 4.

Table 4: results in the case of risk neutral attitude

	Classifiying set *C(u)*				$c^*(u)$
	c_1	c_2	c_3	c_4	
u_{01}	×	×			c_1, c_2
u_{02}	×		×		c_3
u_{03}	×				c_1
u_{04}			×		c_3
u_{05}	×				c_1
u_{06}		×		×	c_2
u_{07}	×	×			c_2
u_{08}	×				c_1
u_{09}	×			×	c_1
u_{10}				×	c_4
u_{11}		×		×	c_4
u_{12}	×				c_1
u_{13}		×	×		c_3
u_{14}				×	c_4
u_{15}	×				c_1
u_{16}	×				c_1
u_{17}		×	×		c_2
u_{18}	×	×			c_1
u_{19}	×				c_1
u_{20}				×	c_4
u_{21}	×				c_1
u_{22}				×	c_4

From Table 4, the conclusion is that half suppliers (11) should be considered for strategic partnerships because they are classified in class c_1; 5 suppliers should be pruned (they should no longer be considered for the partnership in any level) as they belong to class c_4; 3 suppliers are promising

suppliers that must be supported via supplier development programs (class c_2); and finally 3 suppliers have to be considered for competitive partnerships for some products (class c_3)
A sensitivity analysis can be done in various ways: sensitivity regarding the effect of shapes classifying function q on the final results; effect of C zone and R zone overlapping parameter δ, for instance if this parameter is set to 20% then class c_1 is definitely the class where supplier u_{01} must be included instead hesitation between c_1 and c_2 when $\delta = 10\%$.

FUTURE RESEARCH DIRECTIONS

Fuzzy nominal classification method presented in this chapter is a soft computing technique, that is a technique that exploits the tolerance for impression, uncertainty, partial truth, and approximation to achieve tractability, robustness, low solution cost and better rapport with reality in problems solving. If bipolar approach presented in this chapter permits to reach robust solution, there remains, nevertheless, possible improvements regarding methodologies and modeling tools in order to reach practical usability of this framework in solving real world complex problems. Here are some possible improvements directions.

- **Context**: how decision makers and/or experts view uncertain zone between C zone and R zone on one hand and the shape of classifying function q (that is attitude toward risk) on other hand may depend on their personal situation as well as their behavior environment that we refer to as the context. Indeed, preferences depend on psychological attributes of the person who judges; therefore to dispose of a framework that is as close as possible to human way of deciding this context component should be considered in modeling stage.
- **Psychological parameters**: definition and assessment of attributes as well as social relationships may depend on some psychological parameters such as emotion, fear, confidence, etc.;
- **Dynamics**: as the context sensitive consideration mentioned above, attitude of decision makers and/or experts may vary from one instant to another so that a same problem may be viewed differently by a same decision maker from an instant to another. This dynamicity should be considered in the modeling process to allow parameters variation at each instant.
- **Sensitivity analysis**: to dispose with a robust framework for classification procedure analysis in a real world problem solving, a sensitivity analysis should be considered in order to address how solution structure may vary according to some parameters such as C zone and R zone overlapping size, classifying function shapes through attitude of decision makers toward risk.
- **Implementation**: to be useful for practitioners without computer science, mathematics, or artificial intelligence skills, the approach presented in this chapter must be translated into easily usable software; this is a challenge the author is actually attempting to realize.

CONCLUSION

The problem of fuzzy nominal classification as a concept of decision making for many domains in general and for digital marketing in particular has been considered in this chapter. Designing an appropriate procedure for decision making must rely on a sound concept that aids gathering necessary information. In this work the concept of bipolarity has been the stepping stone of the established procedure. Indeed, given an object to classify and a class, there will be some characteristics or attributes of this object that will act in the sense of including it into that class and other aspects that act in the contrary sense. Relying on this observation, an object will be characterized, with regards to a given class, by two measures: a classifiability measure and a rejectability measure. By doing so many classes may be qualified for classifying a given object because the classifiability measure exceeds the rejectability measures in some sense. Furthermore, classifiability and rejectability zones of a feature characterizing a class may overlap or be separated by a blank zone meaning hesitation of decision makers or experts; using two measures to evaluate the classifiability degree also allow to consider possible hesitation of decision makers and/or experts as many classes may be qualified for inclusion of a given object; these facts render the approach presented in this chapter near to human decision making procedure. This soft computing oriented technique may be useful in many applications in general and digital marketing in particular to cope with uncertainty in general (ignorance, hesitation, doubt, imprecision) and to ensure the robustness of final solution.

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