Weighted OWA (Ordered Weighted Averaging Operator) Preference Aggregation for Group Multicriteria Decisions

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Abstract: - Group decision making is an integral part of operations and management functions in almost every business domain with substantial applications in finance and economics. In parallel to human decision makers, software agents operate in business systems and environments, collaborate, compete and perform algorithmic decision-making tasks as well. In both settings, information aggregation of decision problem parameters and agent preferences is a necessary step to generate group decision outcome. Although plenty aggregation information approaches exist, overcomplexity of the underlying aggregating operation, in most of them, is a drawback, especially for human based group decisions in practice. In this work we introduce an aggregation method for group decision setting, based on the Weighted Ordered Averaging Operator (WOWA). The aggregation is applied on decision maker preferences, following the majority concept to generate a unique set of preferences as input for the decision algorithm. We present the theoretical construction of the model and an application at a group multicriteria assignment decision problem, along with detailed numerical results. The proposed method contributes in the field, as it offers a novel approach that is simple and intuitive, and avoids overcomplexity during group decision process. The method can be also easily deployed into artificial environments and algorithmic decision-making mechanisms.

Key-Words: - Group Decision Making; Weighted Ordered Averaging Operator (WOWA); Multicriteria Analysis; Financial Classification.

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1 Introduction

Group decision making has been studied in a variety of settings and environments for long, and although it might be considered as a mature research domain, it yet remains active and evolving. Key reasons for the interest in the domain include among others the ongoing increasing complexity of real-world problems, the increasing data volumes used as input, the usage of artificial agents that take decisions in collaborative environments instead of humans. All the above make informed decision-making process a challenging task. Recent works [1] demonstrate the extent of the domain and review the direction of theoretical research towards uncertainty, fuzzy sets and rough sets, but also touch upon the challenges in technology adoption [2] of applications and systems in the domain as well.

A subset of group decision research focuses on multicriteria decision problems, as they constitute the majority of real-world settings, where multiple overlapping criteria need to be considered prior to a decision. A variety of methodologies and decision support systems have been introduced with many practical applications, especially in financial domain. Zopounidis et. al. [3] present a thorough review of decision support methodologies focusing mainly on finance and multicriteria settings. What is evident from existing research, is that multicriteria analysis is a valid way to handle inherent complexity of group decisions and model problems with large numbers of parameters and participants, that often leads to overly challenging settings. Salo et. al. reviewed a large number of academic works on multicriteria methods utilization for group decisions and conclude that the potential is very high as multicriteria analysis provides a structured way for problem formulation, guides members to understand requirements effectively and also express their preferences reflecting their individual decision model [4]. Other works also indicate the applicability of multicriteria analysis to assist group decision making in a variety of problems, resulting in numerous methodologies and group decision support systems [5], [6], [7], [8].

In existing research, a group decision problem in multicriteria setting can be modelled under two major approaches:

1) Aggregation of individual decisions. In this approach, individual multicriteria models are developed per decision maker and capture individuals' preferences. Each group member formulates a multicriteria problem defining the parameter values according to her preferences. The model is solved resulting into an individual solution set. Next, the individual solutions are aggregated by aggregation operators providing thus the group solution.
2) Aggregation of preferences. In the second approach, a multicriteria model is developed for the entire team. Each group member defines a set of parameter values that are aggregated by appropriate operators, providing finally a group parameter value set. The muticriteria method is then applied on this group parameter set and the solution expresses group preference.

Both approaches have some positive and negative aspects, related to complexity, information loss, and consensus, to name a few. The aggregation operation that is applied can lead to partial information loss or may be overcomplex for decision makers to understand the impact or contribution of their preferences to the outcome. So, a question that arises in such problems is the choice of the most appropriate aggregation operator or process to express group preferences and process them to reach an acceptable outcome. Several works in the field introduce a variety of approaches, with Yager's work [9], [10] in the nineties being seminal in the field. Yager introduced the Ordered Weighted Averaging family of operators (OWA) and since them it has been used extensively either in multicriteria problems or group decision problems. Since then, additional families of operators have been introduced, including fuzzy and linguistic operators along with various combinations of them. Interested readers are advised to follow the thorough bibliographic analysis of Mesa et. al. [11], that presents a detailed review of the developments in this field reflecting its evolution and directions for the future.

Following the above stream of work, we present here a novel aggregation method for group decision multicriteria classification problems utilizing the Weighted OWA (Ordered Weighted Averaging) operator. The group classification problem refers to the assignment of a set of alternatives in a number of categories. So, having a set of alternatives, a set of categories and a set of evaluation criteria, the aim is to assign alternatives to categories with respect to their score on the evaluation criteria according to group members' preferences. In our approach we utilize WOWA operator for the aggregation of individual preferences calculating an aggregated set of group parameters, that is used as input for the classification algorithm. The multicriteria classification algorithm we use is based on the concept of inclusion/exclusion of an action with respect to a category [12], [13].

The process is briefly the following. The group facilitator proposes a set of parameters to the group members. Next, each group member evaluates the proposed parameter set and expresses her preferences in numeric format. The individual preferences are aggregated by WOWA operator and a set of group parameters is generated. The classification algorithm is applied, using the group parameter set as input, for the classification of alternatives and group members evaluate derived results. In case of low level of group consensus, parameters are redefined partially or in total and aggregation phase is repeated. The method is novel in the field, it is intuitive enough and makes easy for decision makers to interpret and also estimate the impact of their preferences on the result.

In this work we focus on the aggregation procedure of group member preferences, presenting the approach, as well as a detailed numeric example, which demonstrates its applicability to real world problems. Initially, we present necessary theoretical background information on OWA and WOWA operators, as well as a brief overview of the NexClass multicriteria classification algorithm we utilize. The aggregation approach is presented in the next section along with a detailed example and explanations of the steps. Finally, we conclude by summarizing key findings and considerations for the future.

2 Background

2.1 OWA operator (Ordered Weighted Averaging Operator)

OWA operator was initially introduced by Yager [9] and was developed and discussed further in several works since then. It remains a very important and intuitive approach for its simplicity and constitutes the basis for several families of operators that have been introduced since then.

An OWA operator of dimension n is a mapping function $\varphi: \square^n \rightarrow \square$, which has a weighting vector $W = (w_1, \dots, w_n)$ associated with it, such as $w_i \in [0,1], and \sum_{i=1}^{n} w_i = 1$, and aggregates a set of values $\{p_1, \dots, p_n\}$ according to the following expression $\varphi_w(p_1,\dots,p_n)=\sum_{i=1}^{n} w_i\cdot p_{\sigma(i)}$,where $\sigma:\{1,\dots,n\}\rightarrow\{1,\dots,n\}$ is a permutation of set $\{p_1,\dots,p_n\}$, such as $p_{\sigma(i)}\geq p_{\sigma(i+1)}$, $\forall i=1,\dots n-1$, (e.g. $p_{\sigma(i)}$ is the i-highest value in set $\{p_1,\dots,p_n\}$).

A basic property of OWA is the reordering of arguments according to their values, which associates a weight to particular positions in the ordered set of values and not to the values. OWA operators are commutative, monotonic and idempotent, following the basic properties of averaging operators. Weight vector definition is a central issue for the OWA operator, and it impacts the outcome. Yager proposes two methods for its estimation [9]. The first approach uses a kind of training approach using some training data, while the second one assigns semantics on the weights.

Following the second approach, weights can express the concept of fuzzy majority on the aggregation of the values with OWA. In this approach weights can be obtained by using a functional form of linguistic quantifiers. In this case a quantifier is defined as a function $Q:[0.1]\rightarrow[0,1]$ where $Q(0)=0$, $Q(1)=1$ and $Q(x)\geq Q(y)$ for $x\geq y$. For a given value $x\in[0,1]$, the $Q(x)$ is the degree to which x satisfies the fuzzy concept being represented by the quantifier. Based on function Q the OWA weight vector is given by $w_i=Q(\frac{i}{n})-Q(\frac{i-1}{n}), i=1,\dots,n$. Following this approach, the quantifier determines the weighting vector according to the semantics associated with the operator from function Q. Zadeh [9] defined membership function of quantifier Q by the expression $Q(r)=\begin{cases}0, & if\ r<a\\ \frac{(r-a)}{b-a}, & if\ a\leq r\leq b\\ 1, & if\ r>b\end{cases}$ with $a,b,r\in[0,1]$. The most common quantifiers used are 'most', 'at least half', 'as many as possible' with parameters (a,b) equal to $(0.3,0.8),(0,0.5),(0.5,1)$ respectively. For example the fuzzy majority concept can be expressed by using quantifier Q 'most' with values $(a,b)=(0.3,0.8)$ for the calculation of OWA weights.

The fuzzy majority approach with OWA aggregation has been utilized as is or with variations on group decisions, where the objective was the maximization of group consensus, since this approach is more appropriate than simple averaging operators, as it takes into account the majority concept and can model a variety of group settings.

2.2 WOWA operator (Weighted OWA)

WOWA operator was introduced by Torra [14], [15] in order to extend OWA based aggregation in a way to consider weights of sources in addition to weights of values. It has been used in decision support for aggregation of preferences and consensus generation [16], [17], [18].

A WOWA operator of dimension n is a mapping function $\varphi_{WOWA}:\mathfrak{R}^n\rightarrow\mathfrak{R}$, which has two weight vectors associated with it, $W=(w_1,\dots,w_n)$ with $w_i\in[0,1],\sum_{i=1}^{n} w_i=1$, (which expresses the values importance in analogy to OWA weights) and $B=(\beta_1,\dots,\beta_n)$ with $\beta_i\in[0,1],\sum_{i=1}^{n}\beta_i=1$, (which expresses the importance of sources in analogy to a weighted average operator), and aggregates a set of values $\{p_1,\dots,p_n\}$ with the following expression $\varphi_{\mathrm{WOWA}}(p_1,\dots,p_n)=\sum_{i=1}^{n}\omega_i\cdot p_{\sigma(i)}$, where $\sigma:\{1,\dots,n\}\rightarrow\{1,\dots,n\}$ is a permutation of set $\{p_1,\dots,p_n\}$ such that $p_{\sigma(i)}\geq p_{\sigma(i+1)}$, $\forall i=1,\dots n-1$, (e.g. $p_{\sigma(i)}$ is the i-highest value in set $\{p_1,\dots,p_n\}$), and $\omega=(\omega_1,\dots,\omega_n)$ and $\omega_i\in[0,1],\sum_{i=1}^{n}\omega_i=1$ is the weight vector of WOWA operator.

Weights $\omega=(\omega_1,\dots,\omega_n)$ are defined as $\omega_i=$ w*($\sum_{j\leq i}\beta_{\sigma(j)}$)-w*($\sum_{j<i}\beta_{\sigma(j)}$), where $w*$ is a monotone increasing function which interpolates points $(i/n,\sum_{j\leq i} w_j)$ with the point (0,0). Calculation of $w*$ can be executed either from direct definition of function $w*$, or from the definition of the vector $W=(w_1,\dots,w_n)$ initially, and calculation of the interpolation function $w*$ next.

Following the second approach, for the evaluation of the function $w*$ from the weight vector $W=(w_1,\dots,w_n)$ an interpolation method is required. From available methods the one to be used, has to define a monotonous and bounded function (e.g. polynomial) when input data are monotonous and bounded. WOWA operator can be considered as generalization of weighted mean and OWA operators, since for equivalent sources' weights it coincides with OWA, while for equivalent values' weights it coincides with weighted mean.

Although the definition of weights is a process that is not straightforward and can vary among various implementations, the WOWA aggregation approach is intuitive enough WOWA operator is quite efficient for the aggregation of member preferences in group setting. It allows aggregation of values considering members' importance, and the definition of zones of different importance which express variations of majority values.

3. WOWA aggregation method

3.1 Proposed group decision aggregation process

The key focus of this work is the introduction of an aggregation method for group decisions. Specifically, we are interested in classification decisions, where a number of alternatives are assigned to predefined categories, based on the aggregated preferences of a group of decision makers. The decision process can be divided in the aggregation phase, where member preferences are collected and aggregated, and the classification phase, where a classification algorithm is applied in the group preferences. The aggregation phase is linked to the algorithm used in the classification phase, as each algorithm usually requires a set of parameters in a specific format. So, the decision problem formulation is based on the algorithm first, and then the aggregation process generates the appropriate input for the algorithm.

In this work we focus on group classification problems, where categories are nominal and predefined and group members provide their preferences on a number of attributes for the alternatives to be classified. The specific classification setting, has been approached by NexClass classification algorithm [12]. NexClass is a multicriteria method and decision support system that was introduced to address nominal classification problems using the concept of fuzzy inclusion degree [12], and we shall use it in this work for group decision setting for the classification of a set of alternatives into predefined classes according to their performance at a number of criteria.

The inclusion/exclusion of an alternative from a category is determined by evaluating the fuzzy inclusion degree of the alternative for the specific category, following concordance/non-discordance concepts. The categories are defined by an entrance threshold, which can be considered as the least typical representative alternative that satisfies the inclusion requirements. The objective of the algorithm is to classify actions to categories in a way to consider inclusion/exclusion concept.

The application of NexClass algorithm in group classification problems requires the definition of the parameters for a set of decision makers. To use the group parameters as input for the algorithm, appropriate aggregation is required. In this work we use a WOWA aggregation approach to generate the input values for the algorithm.

The following parameters are required for the group decision making process:

1) A set of group decision makers $M = \{m_1, m_2, ... m_n\}$ and corresponding importance weights $B = \{\beta_1, \ldots, \beta_j\}$ assigned to each one.
2) A set of evaluation criteria $F = \{g_1, g_2, \ldots, g_n\}$ generated from problem requirements and their corresponding assigned weights.
3) A set of categories $\Omega = \{C^1, C^2, \ldots, C^h\}$ for the classification of alternatives. Categories are defined by their entrance thresholds b^h and their scores to evaluation criteria $g_j(b^h)$.
4) A set of alternatives $A = \{a_1, a_2, \ldots, a_m\}$ for classification, defined by their performance on the evaluation criteria $\forall a, g(a) = (g_1(a), g_2(a), \ldots, g_n(a))$.
5) Preference, indifference and veto threshold values for each criterion.

In group decision environment we consider that a facilitator drives the process and initiates the parameters and criteria. Facilitator defines the alternatives and evaluation criteria and also assigns member importance weights. In a more generic setting, problem formulation could be also a group process, requiring consensus, but for simplicity we keep it as a separate procedure. However, in the majority of business decisions the problem is more or less structured and decision makers are asked to contribute by providing their preferences. So, after the initiation of parameters facilitator informs members to submit their preferences. In this phase, group members express their preferences on the proposed parameter set. Specifically, group members provide

1) Preferred values for each alternative per criterion for all combinations of criteria and alternatives. Those values reflect their preferences on the alternatives.
2) Preferred values on the threshold per criterion, that define the baseline levels for assignment to a category.

Member preferences are either expressed or converted in numeric values. After the preference collection phase, we apply a WOWA aggregation process for all the individual member values for thresholds and alternatives, and the aggregated values are used as input for NexClass algorithm.

For the calculation of aggregated values with WOWA, we follow the approach below:

1) We consider the fuzzy majority concept (although it can be modified following the problem requirements) and use the values $(a, b) = (0.3, 0.8)$ representing the 'most'

value for the quantifier $Q(r) = \begin{cases} 0, & if\ r < a \\ \frac{(r-a)}{b-a}, & if\ a \le r \le b \\ 1, & if\ r > b \end{cases}$ and evaluate the weights of the OWA operator from the expression $w_i = Q(i/n) - Q((i-1)/n), i = 1, \ldots, n$.

2) Following the approach proposed by Torra [15] we calculate WOWA weights $\omega = (\omega_1, \ldots, \omega_n)$ by interpolating a set of points defined by the set $S = \{(i/n, \sum_{j\le i} w_j) | i = 1, \ldots, n\} \cup \{(0,0)\}$ and calculate the function $w*$ as required

3.2 WOWA aggregation steps

In the following we summarize the proposed aggregation steps for the aggregation of group preferences. A classification problem can be defined by the following initial parameters:

1) A group of members $M = \{m_j\}$,j = 1,...,n as decision makers and corresponding importance weights $B = \{\beta_1, \ldots, \beta_j\}$, j $= 1, \ldots, n$,
2) A set of evaluation criteria $G = \{g_i\}, i = 1, \ldots$, k,
3) A set of categories $C = \{C^i\}$, i = 1,...,m for the classification of actions,
4) A set of alternatives $A = \{a_i\}, i = 1, \ldots$, s for classification.

The objective is to classify the alternatives $A = \{a_i\}$ in appropriate categories $C = \{C^i\}$ with respect to member preferences. The aggregation process is as follows:

Step 1: We consider,

1. Values to be aggregated $\{p_1, \ldots, p_n\}$ as provided by members,
2. Members' weights $B = \{\beta_1, \ldots, \beta_j\}$.

Step 2: We calculate the associated WOWA weights $W = (w_1, \ldots, w_n)$ by means of OWA. For the calculation we consider the fuzzy majority concept and use the values $(a, b) = (0.3, 0.8)$ representing the 'most' value for the quantifier $Q(r) = \begin{cases} 0, & if\ r < a \\ \frac{(r-a)}{b-a}, & if\ a \le r \le b \\ 1, & if\ r > b \end{cases}$ and evaluate the weights of the OWA operator from the expression $w_i = Q(i/n) - Q((i-1)/n), i = 1, \ldots, n$.

Step 3: We calculate WOWA weights $\omega = (\omega_1, \ldots, \omega_n)$ following the approach proposed by Torra [15]. Initially we calculate the set of points that will be connected. This set is defined as $S = \{(i/n, \sum_{j\le i} w_j) | i = 1, \ldots, n\} \cup \{(0,0)\}$. Next the set of points is interpolated and function $w*$ is calculated.

Step 4: With respect to the sets of weights $\omega = (\omega_1, \ldots, \omega_n)$ we aggregate the set of values $\{p_1, \ldots, p_n\}$ as $\varphi_{\text{WOWA}}(p_1, \ldots, p_n) = \sum_{i=1}^{n} \omega_i \cdot p_{\sigma(i)}$.

3.3 Illustrating example

To demonstrate the proposed model and aggregation process, we present a detailed example for a group decision problem, following the steps presented in the previous section. We assume a classification problem with the following initial parameters:

1) A group of seven members $M = \{m_j\}$,j = 1,...,7
2) A set of group member corresponding importance weights as $B = \{\beta_1, \ldots, \beta_j\} = \{0.2.0.2, 0.1, 0.1, 0.1, 0.2, 0.1\}$,
3) A set of eight evaluation criteria $G = \{g_i\}, i = 1, \ldots, 8$,
4) A set of four categories $C = \{C^i\}$, i = 1,...,4 for the classification of actions,
5) A set of six alternatives $A = \{a_i\}, i = 1, \ldots, 6$ for classification.

The objective is to classify the alternatives $A = \{a_i\}, i = 1, \ldots, 6$ in appropriate categories $C = \{C^i\}$, i = 1,...,4, with respect to member preferences on alternatives performance on the evaluation criteria. In general group members provide values for a series of parameters that we aggregate to reach to a group value. In the following we present the aggregation approach as applied only to criteria acceptance and criteria weights, since the same procedure is applied to the rest of values.

Step 1: Initially, each member m_j expresses his opinion indicating acceptance level in a linguistic scale {Extremely High, High, Medium, Low, Extremely Low}, on the set of criteria g_j. These values are converted to numeric values ranging from 5 to 1 as below.

$$[g_{ij}] = \begin{bmatrix} 5 & 5 & 4 & 5 & 4 & 4 & 4 \\ 4 & 2 & 3 & 1 & 2 & 1 & 2 \\ 5 & 5 & 3 & 4 & 5 & 3 & 4 \\ 3 & 5 & 3 & 4 & 5 & 4 & 5 \\ 2 & 4 & 3 & 4 & 5 & 5 & 4 \\ 4 & 4 & 5 & 4 & 5 & 5 & 5 \\ 5 & 4 & 5 & 5 & 5 & 5 & 5 \\ 1 & 3 & 2 & 3 & 1 & 2 & 2 \end{bmatrix}.$$

Step 2: We calculate the associated WOWA weights $W = (w_1, \ldots, w_n)$ by means of OWA. For the calculation we consider the fuzzy majority concept and the resulting values are as follows:

I	W
1	0
2	0
3	0.257
4	0.285
5	0.285
6	0.171
7	0

Step 3: The set of points $S = \{(i/n, \sum_{j \le i} w_j) | i = 1, \ldots, n\} \cup \{(0,0)\}$ for the interpolation function is calculated as

$i = 1$, $(\frac{1}{7}, \mathrm{w}_1) = (\frac{1}{7}, 0)$

$i = 2$, $(\frac{2}{7}, \mathrm{w}_1 + w_2) = (\frac{2}{7}, 0)$

$i = 3$, $(\frac{3}{7}, \mathrm{w}_1 + w_2 + w_3) = (\frac{3}{7}, 0.257)$

....

$$i = 7, (\frac{7}{7}, \mathrm{w}_1 + w_2 + w_3 + \ldots + w_7) = (\frac{7}{7}, 1) = (1,1)$$

Based on these points the interpolation function is $w*$ is calculated using the algorithm used by Torra [15]. Next, we calculate the set of WOWA weights $\omega = (\omega_1, \ldots, \omega_n)$ as follows:

$i = 1$, $\omega_1 = \mathrm{w}^*(p_1) = \mathrm{w}^*(0.2)$

....

$i = 7$, $\omega_7 = \mathrm{w}^*(\sum_{i=1}^{7} p_i)$-$\mathrm{w}^*(\sum_{i=1}^{6} p_i)$

WOWA weights are thus $\omega = \{0, 0.2032, 0.1962, 0.1994, 0.1994, 0.1995, 0\}$.

Step 4: Next WOWA values are calculated as $\varphi_{\mathrm{WOWA}}(p_1, \ldots, p_n) = \sum_{i=1}^{n} \omega_i \cdot p_{\sigma(i)}$. For example for the first criterion we have $\varphi_{\mathrm{WOWA}}(5,5,5,4,4,4,4) = 0 * 5 + 0.2032 * 5 + 0.01962 * 5 + 0.1994 * 4 + 0.1995 * 4 + 0.1995 * 4 + 0 * 4 = 4.3915$

Aggregation result for the set of criteria is the following:

$[g_{ij}] = \begin{bmatrix} 4.3915 \\ 1.8159 \\ 4.1919 \\ 3.9957 \\ 3.7595 \\ 4.3915 \\ 4.9376 \\ 1.8159 \end{bmatrix}$, while results using OWA and Weighted mean aggregation are $[g_{ij}] = \begin{bmatrix} 4.249 \\ 1.825 \\ 4.077 \\ 4.077 \\ 3.82 \\ 4.534 \\ 4.99 \\ 1.825 \end{bmatrix}$ and $[g_{ij}] = \begin{bmatrix} 4.5 \\ 2.2 \\ 4.2 \\ 4.1 \\ 3.8 \\ 4.5 \\ 4.8 \\ 2.0 \end{bmatrix}$ respectively.

Acceptance result for criteria g_2 and g_8 are relative low and thus are excluded from problem We follow the same procedure for categories.

Members' m_j preferences on criteria weights w_i are expressed on numeric values as:

$$[w_{ij}] = \begin{bmatrix} 18 & 15 & 14 & 15 & 16 & 19 & 20 \\ 28 & 33 & 26 & 30 & 25 & 23 & 21 \\ 7 & 5 & 9 & 8 & 10 & 9 & 11 \\ 15 & 12 & 13 & 12 & 16 & 16 & 12 \\ 11 & 9 & 14 & 8 & 5 & 9 & 6 \\ 21 & 26 & 24 & 27 & 28 & 6 & 30 \end{bmatrix}, i = 1,\ldots,6, j = 1,\ldots,7$$

Aggregation results are depicted in the table below (Table 1), compared to results from alternative aggregation approaches.

Table 1. Aggregation results

OWA	Weighte d Mean	WOWA	Arithmetic Mean
16.055	16.900	16.417	17
27.717	27.000	26.030	27
8.370	8.000	7.894	8
13.055	13.890	13.417	14
8.199	9.100	8.732	9
25.343	25.100	24.659	26

The above steps are then repeated for all parameters: criteria, actions' scores, categories' thresholds as well as indifference, preference and veto thresholds. Then the aggregated actions' scores, criteria weights and categories' thresholds, is the input parameter set for the multicriteria classification algorithm, which is applied next.

4. Conclusion

Group decision making is a very critical part of today's automated or semi-automated procedures in large systems and settings. Apart from humans, robots and algorithms are also taking part in decisions, with some involving critical ones. As such the domain of group decision making needs to provide appropriate algorithms and procedures for both agent types especially for automated decision making. Aggregation of information is of critical importance, as it can infer bias in the process. Many works propose complex approaches, that lack intuition and are not easy to be adopted by group members. In this work we propose a methodology for aggregation that is based on the intuitive majority rule and we utilize an operator from the OWA family. Group decision problems are inherently complex, but we believe that this approach has merits and can be easily communicated to group members.

We focused on classification decisions, where aggregation of members' preferences is executed at the parameter level and used WOWA operator for the aggregation of individual values. We presented details of the aggregation methodology as well as a detailed example for a classification problem demonstrating its usage for real life problems. The methodology can be easily applied to support group decisions in a variety of environments as it is intuitive and easy to explain to decision makers. However, since the methodology requires a relative substantial number of parameters, it is possible that group members who are not familiar enough with the methodology will be confused. Thus, the number of criteria and parameters should be kept to a number, which will minimize complexity without however loosing critical problem parameters.

This approach can be included in automated decision settings for classification decisions, where software agents can be utilized. It is an emerging field and developments in algorithmic decision making clearly demonstrate this directions. So, this work will be further developed in the future to reach a wider domain and become more parametric, so as to be included in a software system or become part of some intelligent software agent.

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