Methodology and Multicriteria Algorithm for Group Decision Support in Classification Problems

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Abstract: - In this work, a Group Decision methodology and algorithm for small collaborating teams is introduced. It is based on a multicriteria algorithm for classification decisions, where aggregation of member preferences is executed at the parameter level. The algorithm applies to relatively well-structured problems guided by a process facilitator. Initially, a set of parameters is proposed by the facilitator to the group and next group members evaluate the proposed parameter set and express their preferences in numeric or linguistic format. Individual preferences are aggregated by appropriate operators, and a set of group parameter values is generated, which is used as input for the classification algorithm. NeXClass multicriteria classification algorithm is used for the classification of alternatives, initially at a training set of alternatives and later at the entire set. Finally, group members evaluate results, and consensus, as well as satisfaction metrics, are calculated. In case of a low acceptance level, problem parameters are reviewed by the facilitator, and the aggregation phase is repeated. The methodology is a valid approach for group decision problems and can be utilized in numerous business environments. The algorithm can be also utilized by software agents in multiagent environments for automated decision-making, given the large volume of agent-based decision-making in various settings today.

Key-Words: - group decision support, NexClass algorithm, WOWA, OWA, multicriteria classification

Received: July 5, 2022. Revised: August 21, 2023. Accepted: September 26, 2023. Published: November 20, 2023.

1 Introduction

Group Decision Support (GDS) is an active research domain that has gained significant attention during past decades due to its wide application in business domains and automated agent-based decision-making. Research in decision support systems aims to equip decision-makers with tools and methods and assist them in optimizing their decisions. Since a decision support system must reflect decision makers' preferences or their decision model, building a Group Decision Support System (GDSS) is not a trivial and straightforward process. Moreover, several dimensions must be considered as well, such as preference modeling, negotiation, and coordination protocols, to name a few. Several methodologies and tools have been developed to support groups, ranging from collaborative techniques to negotiation ones, depending on whether group members share a common goal or support individual goals. Technologies utilized for GDSS development tend to follow Information Technology advances, resulting in data-driven support systems, that we can meet nowadays. Incorporation of web and mobile technologies can also support collaboration features in real-time, a capability that could not be implemented in the early days of GDSSs, [1]. A variety of methods have been utilized for GDS ranging from algorithmic in well-defined problems, to less structured ones for problems requiring brainstorming and negotiation. Multicriteria analysis methods have also been utilized in various decision problems, however, due to the inherent complex nature of group decision settings there is no unique formulation and solution. In GDS, the multicriteria analysis approach offers a structured way for problem formulation and can guide members to understand all requirements and express their preferences effectively reflecting their decision model, [2]. Despite its merits, multicriteria analysis and relevant methodologies are rarely utilized in group decision research. Reasons for this can be partially attributed to the complexity of aggregating mechanisms as well as negotiation and consensus modeling requirements. Given the limited number of works in this domain and considering the need for automated agent-based decision-making, this work aims to address the gap and introduce a structured methodology that is based on multicriteria analysis and supports group classification decisions.

In brief, the objective of the proposed method is to assign a set of candidate alternatives to several predefined non-ordered categories, according to their ranking on a set of evaluation criteria, defined by a group of decision-makers. Initially, a set of parameters is defined by group members, and next, each group member ranks the proposed parameter set and expresses her preferences in numeric or linguistic format. Individual preferences are aggregated by aggregation operators, and a group parameter set is produced and used as input for the classification algorithm. NeXClass multicriteria classification algorithm is used for the classification of candidate alternatives, initially at a training set of alternatives and later at the entire set. Finally, group members evaluate results, and consensus, as well as satisfaction metrics, are calculated. In case of a low level of group consensus, problem parameters are redefined by group members, and the aggregation phase is repeated. The process can be administered by a group facilitator role or can be automatically run by group members.

In this work, we present the algorithm and the way it can be used in a GDS problem. The structure of the work is as follows. Initially, the introduction sets the aims and highlights the approach. Next, some brief background information is presented on group decisions. Following this, we present the group decision multicriteria methodology in detail. In the next section, we illustrate its usage and applicability in the context of a GDSS and end with a discussion and future research.

2 Background

Group decision-making is an essential component of enterprise strategic planning and operations for many organizations today. Complexity in a business environment requires a decent level of knowledge from a wide range of domains, so the contribution of a domain experts' team is the only way to achieve efficiency in decisions. To support group needs, researchers work towards developing tools and methodologies, ranging from collaboration technologies to decision support systems. Although traditional decision support systems may look outdated in the cloud and big data era today, research is very active and evolves, as data-driven models combined with machine learning developments lead to novel approaches in the field, [3], [4] [5].

Group decisions are inherently more complex compared to single decision-making since several contradicting factors are involved such as individuals' personal opinions, goals, and stakes, resulting in a social procedure, where negotiation and strategy play a critical role. Group decision-making in real business environments also raises some issues, such as conflicting individual goals, not efficient knowledge, validity of information, and individuals' motivation, [6]. Despite the inherent complexity, within a group decision-making setting a member can express personal opinions and suggest solutions from a personal perspective. In addition, negotiation and voting advance decision efficiency and increase consensus and adoption since all participants have contributed to the result, smoothening thus any disputes. In general, group members can be motivated by individual perceptions to work within the group either towards collaboration or towards competition. While in the first case, members express similar opinions and goals, in the second one they state opposing opinions. Although collaborative teams work towards a common goal, contradiction may also occur, [7]. Some key techniques that have been acquired to facilitate group work and decisions include brainstorming, nominal group technique, Delphi method, voting, and multicriteria analysis.

In general, multicriteria analysis can be incorporated as a method to model preferences and facilitate decision-making within a group of decision-makers. Modeling under a multicriteria setting can be formulated under two major approaches. Either as individual multicriteria models, where separate solutions are generated and aggregated into a group solution. Or, as one multicriteria model, where group member preferences are aggregated resulting in a group parameter set that is the input for a multicriteria method. Each approach has merits, and the selection depends on the problem under study. A recent systematic review can be found in the work of [8], where we can see that most of the approaches provide support to sorting and selection decisions. Also, the Analytic Hierarchy Process methodology is a popular method and web technologies are relatively limited. Following the above and given the limited number of works in the domain, we argue that our approach provides a useful tool to decision-makers, filling the gap in group classification decision problems.

2.1 Fuzzy Majority

The majority notion, which is usually defined as a threshold number of individuals, is a widely used crisp criterion in group decisions and aggregation operations. The fuzzy majority, on the other hand, is a soft majority concept expressed by a fuzzy quantifier, which is manipulated via a fuzzy-logic-based calculus of linguistically quantified propositions and can be represented by fuzzy quantifiers, [9]. One such approach is the Ordered Weighted Averaging (OWA) operator, which reflects fuzzy majority by means of fuzzy quantifiers.

The concept of fuzzy quantifiers was introduced by, [10]. This study suggested that the semantics of a fuzzy quantifier can be captured by using fuzzy subsets for its representation. He distinguished between two types of fuzzy quantifiers, absolute and proportional or relative. Absolute quantifiers are used to represent amounts that are absolute such as “about 2” or “more than 5”. These absolute linguistic quantifiers are closely related to the concept of the count or number of elements. He defined these quantifiers as fuzzy subsets of the non-negative real numbers. In this approach, an absolute quantifier can be represented by a fuzzy subset Q, such that for any r the membership degree of r in Q, $Q(r)$, indicates the degree to which the amount r is compatible with the quantifier represented by Q. Proportional quantifiers, such as “most”, and “at least half”, can be represented by fuzzy subsets of the unit interval, [0, 1]. For any $r \in [0,1]$, $Q(r)$ indicates the degree to which the proportion r is compatible with the meaning of the quantifier it represents. Any quantifier of natural language can be represented as a proportional quantifier or given the cardinality of the elements considered, as an absolute quantifier.

Fuzzy quantifiers are usually of one of three types, increasing, decreasing, and unimodal. A non-decreasing quantifier Q satisfies the expression $\forall a,b \text{ if } a > b \text{ then } Q(a) \geq Q(b)$ and its membership function is given by the following expression $Q(r) = \begin{cases} 0, & \text{if } r < a \\ \dfrac{(r-a)}{b-a}, & \text{if } a \leq r \leq b \\ 1, & \text{if } r > b \end{cases}$ with $a,b,r \in [0,1]$. For our algorithm, we select the following values which represent the concept of fuzzy majority $(a,b) = (0.3,0.8)$.

2.2 Social Judgement Scheme

The aggregation of individual preferences in a group decision setting has been studied extensively. Davis has introduced the Social Decision Scheme (SDS) theory providing a formal way to analyse different aggregation processes by representing them as stochastic matrices called decision schemes. SDS theory suggests a systematic way to investigate which decision aggregation model best defines the actual consensus process in a given context, [11], [12]. In addition to the SDS approach Davis proposed the Social Judgment Scheme (SJS) theory, which applies to continuous judgment cases. This model assumes a dominant role of members whose opinions are relatively central in the group. Thus, each decision-maker is given a weight depending on the centrality of his/her position relative to the other members of the group and the group decision is a weighted sum of the members’ preferences. This model has been tested empirically with sufficient results, [12]. In our model, we implement the SJS model for aggregating numeric values assigned by decision-makers to problem parameters.

For example, we consider the case where a decision maker expresses her individual opinion on the weight of a criterion in numerical format. If w_{ij} is the weight of ith criterion as defined by jth decision maker, then the group weight c_i of ith criterion is defined as $c_i = \sum_{j=1}^{n} v_{ij} w_{ij}$ where v_{ij} is the consensus weight of jth decision maker relative to ith criterion. Consensus weight depends on how close the position of a decision maker’s opinion with respect to the rest of the members’ opinions is. The closer the opinion of the decision maker to the team’s opinion is, the greater weight is calculated for this decision maker for the specific criterion. Consensus weights are calculated according to the formula $v_{ij} = \dfrac{\sum_{l=1, l \neq j}^{n} \exp(-|w_{ij} - w_{il}|)}{\sum_{j=1}^{k} \sum_{l=1, l \neq j}^{n} \exp(-|w_{ij} - w_{il}|)}$.

3 Proposed Group Decision Methodology

The main objective of this work is to introduce a method to support a group of decision-makers in classification problems. The problem refers to the assignment of a set of alternatives to several predefined non-ordered categories, according to their ranking on a set of evaluation criteria. For this reason, we have developed a structured group decision methodology, based on the following principles:

- *The decision group is a small homogeneous team of collaborating decision makers*. Although the methodology can be extended to large decision teams, our approach is based on collaborative teams, which target maximizing consensus. Non-collaborative teams require a negotiation-based approach, which is out of the scope of the present methodology.
- *A facilitator coordinates the entire decision process*. The entire group decision process is coordinated by a facilitator. Usually, in group decision making a negotiation phase takes place at the preliminary steps of the decision problem formation. During this negotiation, which can be either structured or not, basic parameters are defined. Since our methodology does not focus on group formation procedure and initial negotiations, we consider that a preliminary negotiation step has already taken place, possibly by utilizing a brainstorming technique, between stakeholders, and the outcome of this process is an initial set of proposed parameters. This set is expressed by the facilitator as the initial proposal upon which group members will express their preferences. The facilitator drives the entire process to generate efficient and timely results.
- *A decision problem is structured or semi-structured*. The team solves a structured classification problem based on their personal preferences. Non-structured problems are out of scope.
- *A multicriteria analysis is utilized for the classification*. For the classification problem, we utilize multicriteria analysis which provides appropriate support to this type of problem.

Following the above principles, we developed a group decision methodology comprising the following phases:

- *Problem initiation*. In this phase, the facilitator defines the basic parameters of the problem. The parameters are related to the specific multicriteria methodology and refer to criteria, alternatives, and categories.
- *Aggregation of individual parameters*. During this phase, each member evaluates the proposed parameter set and expresses her preferences in numeric and linguistic format. Next, individual preferences are aggregated, and a group parameter set is produced which is used as input for the classification algorithm.
- *Application of NexClass multicriteria classification algorithm*. In this phase, using the group parameter set, the NexClass multicriteria algorithm is applied initially to a training set of alternatives, [13]. Group members evaluate results and if accepted, the same parameter set is used for the classification of the entire set of alternatives.
- *Results evaluation.* At this phase, group members evaluate the classification results of the entire set expressing their opinions.

3.1 Phases

Notations used:

- $A = \{a_1, a_2, ..., a_m\}$: a set of alternatives for classification in a number of categories,
- $G = \{g_1, g_2, ..., g_n\}$: 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 the category.
- Alternatives' performance on criteria is calculated in a way such that $\forall a, g(a) = (g_1(a), g_2(a),..., g_n(a))$ and $\forall b_i^h, g(b_i^h) = (g_1(b_i^h), g_2(b_i^h),..., g_n(b_i^h))$

Phase 1. Problem initiation. In this phase the facilitator initiates the decision problem, defining all appropriate parameters. In details:

1. Basic parameters. Initially, the facilitator defines several parameters, related to the classification problem such as the number of group members, the number of categories, the number of criteria, and to results assessment such as the consensus, satisfaction, and acceptance levels. These levels define the minimum required levels for the group decision. In case they are not satisfied, a second round is executed with modification of individual preferences.
2. Members. The facilitator defines group members $\mathrm{M} = \{\mathrm{m}_1, \mathrm{m}_2, ...\mathrm{m}_\mathrm{n}\}$ assigning all necessary contact details.
3. Categories. The facilitator defines the set of categories $C = \{C^1, C^2, ..., C^h\}$ for the classification of alternatives.

4. Evaluation criteria. The facilitator defines the set of evaluation criteria $G = \{g_1, g_2, ..., g_n\}$ according to problem requirements.
5. Criteria weights. The facilitator defines the criteria weights.
6. Alternatives. The facilitator defines the set of alternatives $A = \{a_1, a_2, ..., a_m\}$ for classification and defines their performance on the evaluation criteria $\forall a, g(a) = (g_1(a), g_2(a), ..., g_n(a))$
7. Entrance thresholds. The facilitator defines appropriate entrance thresholds $B^h = \{b_1^h, b_2^h, ..., b_k^h\}$ for each category $C = \{C^1, C^2, ..., C^h\}$ For each threshold the facilitator defines preference, indifference, and veto thresholds.
8. Training set. The facilitator defines a subset of alternatives as a training set, to evaluate the parameters' accuracy. After the initiation of the parameters, the facilitator communicates through the GDSS with group members informing them about the problem and asking them to submit their preferences.

Phase 2. Aggregation of individual parameters. In this phase group members express their preferences on the proposed parameter set. Member preferences are expressed in numeric values and linguistic preferences. For the aggregation of numeric values, we utilize the Social Judgment Scheme (SJS), while linguistic terms are aggregated in terms of an Ordered Weighted Averaging Operator (OWA), [13].

1. Numeric value aggregation. For numeric values, we follow the SJS approach as presented in the previous section.
2. Linguistic value aggregation. For non-numeric values, we follow the Ordered Weighted Averaging Operator (OWA) approach introduced in, [13].

Aggregation of member preferences is executed for the following parameters.

1. Criteria. Group members express their acceptance of each proposed criterion on a five-point linguistic scale and their preferred weight in numeric value.
2. Alternatives. Group members express their acceptance of alternatives' performance or submit their preference in numeric value.
3. Categories. Group members express their acceptance of each category definition and submit their preferences on category thresholds in numeric value.

The facilitator proceeds with the validation of members' input and aggregates the values. Parameters with low acceptance levels are marked and are subject to review if the final results are not acceptable to group members.

Phase 3. Application of multicriteria classification algorithm. After the aggregation of individual members' parameters, a group parameter set is created and the NeXClass algorithm for multicriteria classification is applied to this group parameter set, [13].

NeXClass algorithm classifies an alternative to a specific category with respect to the alternative's performance to the evaluation criteria, considering a set of alternatives, a set of predefined non-ordered categories, and a set of evaluation criteria. In more detail, the algorithm works as follows:

1. For each category $C = \{C^1, C^2, ..., C^h\}$, the decision maker defines an entrance threshold $B^h = \{b_1^h, b_2^h, ..., b_k^h\}$ using available information. This threshold represents the minimum requirements for an alternative in terms of performance on the evaluation criteria to be included in this category.
2. The decision maker defines the alternatives' performance $\forall a, g(a) = (g_1(a), g_2(a), ..., g_n(a))$ on the evaluation criteria $F = \{g_1, g_2, ..., g_n\}$.
3. For each alternative, an excluding degree $\gamma_i^{tot} = \dfrac{\gamma_i\,(b_i^h, a)}{1 + \gamma_i\,(a, b_i^h)}$ is calculated for every category threshold, based on outranking relations, following a similar approach to the ELECTRE TRI method.
4. Next, the fuzzy excluding degree $\gamma(a, C^h) = P(a, b^h) = \gamma^{tot}$ of an alternative $a \in A$ over a category $\mathrm{C^h} \in C$ is calculated.
5. Assignment to a category is based on the 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 $\mathrm{C^h} \in C$ for which the excluding degree over the entrance threshold is minimum.

Application of the NeXClass classification algorithm is executed through the following steps.

1. Training set classification. The classification algorithm is initially applied to the training set, as it has been defined by group members. Classification is executed by the Facilitator, and group members are informed to assess the results.
2. Evaluation of results. Each member expresses her preference for the results on a five-point linguistic scale, and in case of a low acceptance level, the Facilitator executes a second round of parameter definition from members to calibrate the model. When training set classification is acceptable, the Facilitator proceeds with the classification of the entire set of alternatives. In case of a low acceptance level after the second round, the Facilitator terminates the process to revise the problem with stakeholders.
3. Training set classification. The classification algorithm is finally applied to the entire set by the Facilitator, and group members are informed to assess the results.

Phase 4. Results assessment. Group members assess the results expressing their preference in a five-point linguistic scale. In case of a low acceptance level, the Facilitator reruns the model, requesting modifications from members.

3 Discussion

In the previous sections, we introduced a novel methodology for group classification decisions in nominal categories, based on the multicriteria algorithm NeXClass for the aggregation of individual preferences. The approach aggregates the individual preferences under the fuzzy majority approach and the resulting set is used as input for the classification algorithm. At the end of the process, consensus is measured and if it does not reach the baseline the process is repeated. An alternative approach would be to apply the classification algorithm at the member level and then aggregate the classification results. This approach is not suitable for nominal categories, as there is not no way to aggregate results on categories, while numeric preferences are easier to aggregate by applying OWA family operators. Examining the scenario of aggregating class preferences will be part of future research on this domain.

As a general comment, the methodology introduced contributes to existing GDS research, as it presents an integrated methodology for group classification problems in small-group settings. The methodology is based on a solid foundation for aggregation of preferences and its structured approach can be easily implemented in a web GDSS or a mobile application. In addition, it can be easily utilized in multiagent-based decision-making and automated decisions in collaborative environments where agents interact and try to reach a consensus.

As mentioned earlier, due to the complex nature of decision problems, it is not feasible to provide a generic methodology that fits all problems, and this is the reason for the diversity of methods in the literature. The methodology presented here is not very specific and can be extended to various applications and generalized as a model to fit more complex scenarios. However, some limitations can be identified in the present form. The following restrictions exist regarding the problems that can be solved by the methodology.

- Since the methodology requires a relatively 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 an optimum number to minimize complexity without losing critical problem parameters.
- Another limitation is that the number of members should be kept within the limits of a small collaborating team. If members are quite a few, anonymity is not so well established since preferences can be easily identified. On the other hand, a large number of members will increase the complexity and extra facilitation will be necessary. A large number of members require alternative aggregation approaches, while very large numbers require a statistical approach or even sampling.

4 Conclusion

In this work, we presented a Group Decision Support System methodology for small collaborating teams based on multicriteria analysis and aggregation operators. It implements a group multicriteria decision methodology for classification decisions where aggregation of members' preferences is executed at the parameter level. We presented the methodology and the steps in detail so it can be easily implemented in software applications, like GDSS based on web or mobile technology, and can be easily integrated within existing business infrastructure or business intelligence context. Future work will focus on empirical findings from the application of the methodology and analysis of user adoption in business environments. We believe that this methodology and a relevant GDSS can be easily deployed to support group decisions in contemporary business environments, either in physical decision-making or in artificial environments with multiagent settings.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Georgios Rigopoulos is the sole author of the work.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.