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Multicriteria aggregating operator adaptation based on decision making context

FOMBA Soumana[1,2], ZARATE Pascale[2], CAMILLERI Guy[3]

1 : Université des Sciences, des Techniques et des Technologies de Bamako (USTTB) - Hamdallaye ACI 2000 - Rue 405 - Porte 359 -BP E423 - Mali
2 : IRIT – Toulouse University – 2 rue du Doyen Gabriel Marty 31042 Toulouse Cedex 9 – France
3 : IRIT – Toulouse University – 118 route de Narbonne 31062 Toulouse Cedex 9 – France

Soumana.Fomba@irit.fr, Pascale.Zarate@irit.fr, camiller@irit.fr
web-page: http://www.irit.fr/

ABSTRACT

Recommender systems aim to support decision-makers by providing decision advice. We review briefly tools of Multi-Criteria Decision Analysis (MCDA), including aggregation operators that could be the basis for a recommender system. Then we develop a generic multi-criteria recommender system, to support decisions by aggregating measures of performance contained in a performance matrix. To determine a total order of alternatives, the system uses different multicriteria aggregation operators depending on the context of use of the system. Thus, recommendations are calculated using partial preferences provided by the decision maker and updated by the system. An integrated web platform is under development.

Keywords: Recommender System, Choquet Integral, MCDA, Sugeno Integral, Aggregation operator

INTRODUCTION

Recommender systems are designed to help decision-makers make the best possible decisions from a wide range of choices. This process of finding the best solution passes through an inescapable step that is the aggregation of the performances of each alternative according to the preferences of the decision maker. For this purpose, there are several multicriteria aggregation operators of preferences. The choice of the aggregation operator in a decision-making problem is therefore crucial.

We propose in this paper a generic recommender system where the choice of the aggregation operator is implicit and transparent for the user. Among these operators are the weighted sum, the ordered weighted sum, the Choquet integral, the Sugeno integral [1], and so on. These operators are classified into two main categories, namely quantitative and qualitative, when they are respectively a decision problem where assessments are quantitative or qualitative [2]. The choice of an operator in a category uses a collaborative recommendation model and a similarity model between decision problems.

This article is structured as follows: we make a brief presentation of some aggregation operators in the first section. In the second section, we present our generic multicriteria recommender system. The third section deals with the results obtained by this system. And finally, we open the discussion and possible prospects to these works.

NOTATION AND FORMALIZATION OF THE PROBLEM

We have the following data:

- Set of alternatives A={a,b,c..} with |A|=m. The alternatives represent the different solutions or choices available to a decision-maker faced with a problem of decision-making.
- Set of criterions $\mathbb{N}$={1,2,3,..} with $|\mathbb{N}|$ =n. Criteria can be considered as attributes or characteristics of alternatives. Indeed each alternative is evaluated according to each criterion describing it.
- Numerical values taken by the alternatives for each criterion : $\forall j \in \mathbb{N}, \forall a \in A, a_j$
- Set of the profiles of the alternatives which is a set of vectors such that ∀a A we associate the vector $a=(a_1,a_2, \ldots, a_n) \in \mathbb{R}^n$

Tableau 1: Representation of the performance matrix

Alternative	**Attr. 1**	**Attr.2**	**...**	**Attr.n**	**Aggregated values**
a	a_1	a_2	…	a_n	A(a)
b	b_1	b_2	…	b_n	A(b)
…	…	…	…	…	…

- Let $\succeq$ be a relation on *X* representing the decision-maker's preference. ($\succeq$ is usually pronounced "at least as good as".) As a binary relation, $\succeq$is usually assumed reflexive. For alternatives *a* and *b*, $a \succeq b$ to mean that *a* is preferred to *b*.

AGGREGATION OPERATORS

In decision support, an aggregation operator is usually used to determine an overall score for an alternative from its local performance on the criteria and the user's preferences over criteria, in order to compare it to other alternatives. With the overall score, a ranking can be established that will guide the decision-maker's decision. In this section, we examine several aggregation operators used in the recommender system. These operators belong to two distinct categories, namely quantitative and qualitative.

The Choquet Integral

Aggregation operators such as weighted sum and OWA are unable to model interactions because they depend on weight vectors. What is needed is a non-additive function that defines a weight, not only for each criterion, but also for each subset of criteria. These non-additive functions can thus model both the importance of criteria and the positive and negative synergies between them. A suitable aggregation operator can be based on the Choquet integral [3, 4] that uses non-additive functions that Sugeno proposed be called fuzzy measures [5]. The Choquet integral is used for quantitative evaluations.

The Choquet integral is defined as follows: Let μ be a fuzzy measure on *N*. The Choquet integral of $x \in R^n$ with respect to μ is defined by:

$$C\mu(x) := \sum_{i=1}^{n} x_{(i)}[\mu(A_{(i)}) - \mu(A_{(i+1)})] \tag{1}$$

where (.) denotes the permutation of the components of $x = (x_1, \ldots, x_n)$ such that $x_{(1)} \leq \ldots \leq x_{(n)}$. As well, $A_{(i)}=\{(i), \ldots, (n)\}$ and $A_{(n+1)} = \emptyset$.

The Choquet integral gives the possibility to calculate the index of interaction between the criteria and the global importance of each criterion, called the Shapley value. For more information see [6]

The Sugeno integral

Unlike the Choquet integral which uses quantitative evaluations, the Sugeno integral is used for qualitative evaluations. The integral of Sugeno has been introduced in [5]. We consider here the integral of Sugeno in its discrete version, applied to the aggregation of preference. We also consider a totally ordered set L, not necessarily a numerical one, which is called an evaluation scale, and whose minimum and maximum elements are denoted by 0 and 1 respectively. Sugeno integral is defined in relation to a capacity on the set N which is a function:

$\mu : 2^n \rightarrow L$ such as : $\mu(\emptyset) = 0$ and $\mu(N) = 1$, for $I \subseteq J \subseteq N : \mu(I) \leq \mu(J)$.

For any set of criteria $I \subseteq N$, the value of μ (I) can be interpreted as the degree of importance associated with I.Let a capacitance $\mu: 2^n \rightarrow L$. The integral of Sugeno defined with respect to μ, denoted by S_μ, is expressed in the form

$$S_\mu(y_1, y_2, \ldots, y_n) = \bigvee_{i=1}^{n} \left(y_{(i)} \bigwedge \mu(\{(i), \ldots, (n)\}) \right) \tag{2}$$

where (.) denotes the permutation of the components of $y = (y_1, \ldots, y_n)$ such that $y_{(1)} \leq \ldots \leq y_{(n)}$. By this formula it is seen in particular that μ determines S_μ entirely and uniquely. The problem of learning an integral of Sugeno S_μ can therefore be reduced to that of learning the corresponding capacitance μ.

DESCRIPTION OF THE RECOMMENDER SYSTEM

The proposed recommender system can both treat quantitative evaluations using aggregation operators such as the weighted sum, the ordered weighted sum [7], the Choquet integral, and so on, but also qualitative evaluations using the integral of Sugeno. When creating a decision problem, the user is asked to specify the type of problem choosing whether it is a problem where the evaluations are quantitative or qualitative. The number of criteria involved and the description of each criterion are also asked. Then comes the enumeration of the different alternatives and their score for each criterion. Finally, the user is asked to define a partial order on a subset of alternatives. This partial order is used to define the user's preferences between pairs of alternatives. The whole of this information on the problem of decision support is thus stored in a database while disregarding the aggregation operator to be used for the search for a possible better solution.

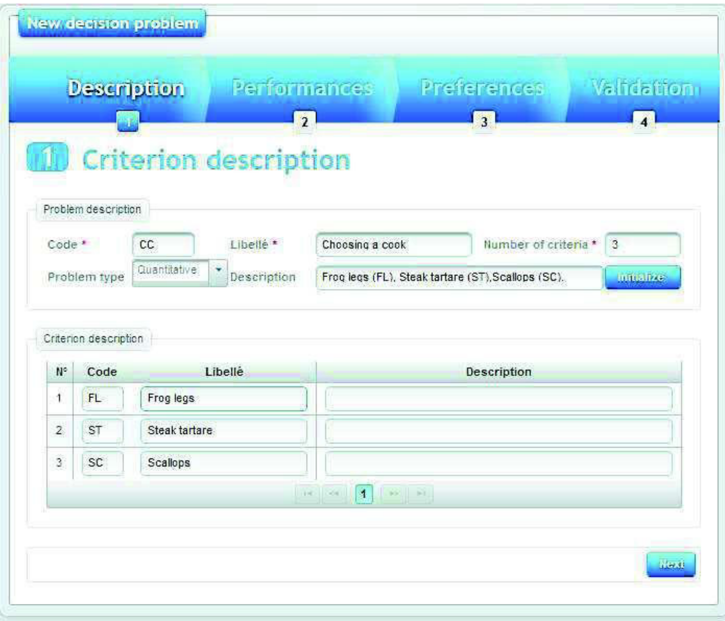

Figure 1: New decision problem

In this window, the first step allows to describe the new problem of decision support, as well as his different criteria. The second step, called Performance, allows us to enumerate the different alternatives and their evaluation for each criterion, called the performance matrix. The third step, called Preferences, allows you to define preferences between pairs of alternatives. And finally the fourth step and last, validates all of this information by saving them in the database.

After collecting data on the decision problem, the parameters of the chosen aggregation operator can compute. Depending on the type of problem (quantitative or qualitative), the choice of the aggregation operator will be based on the concerned category.

In the case of a decision problem, an aggregation operator is chosen in a category based on its effectiveness on similar decision problems. This is done by using a collaborative recommender system [8, 6] and by establishing a similarity model between decision problems. This similarity measure classifies decision problems into three broad categories depending on the nature of the problem. These are the questions of choice, sorting and storage, for more information [9]. The selected aggregation operator is tested by trying to determine its parameters from the preferences of the user. If the parameters of this operator happen to be elicited respecting the set of preferences of the user, then it is proposed to the user, if not, another operator in the same category is chosen on the same bases. This procedure allows the user not to worry about the choice of the aggregation operator in the face of a decision problem and to obtain the best operator in the context of the use of the system.

A WEB PLATFORM RECOMMENDER SYSTEM:

We illustrate the system using following example. Four Chefs, a problem proposed by Marichal & Rubens [10]. We want to evaluate the chefs based on their ability to prepare three dishes: Frog legs (FL), Steak tartare (ST),Scallops (SC). The evaluation of the 4 chefs A, B, C, and D for each dish is given on a scale 0 to 20 in the following performance matrix:

Tableau 2: Evaluations of cooks

	FL	ST	SC
A	18	15	19
B	15	18	19
C	15	18	11
D	18	15	11

Reasoning of the decision maker:

- When a chef is known for his preparation of Scallops, it is better that he prepares Frog Legs well, as compared to Steak Tartare;
- Conversely, when a chef does not do a good job preparing Scallops, it is better that he prepares Steak Tartare well, as compared to Frog Legs.

Thus we can conclude than the decision-maker's ordering is A ≥ B ≥ C ≥ D.

Figure 2:Results obtained by the recommender system on this decision problem

Results: one can easily check that the decision maker's preferences were taken into account.

CONCLUSION

Without being exhaustive, we presented some multicriteria aggregation operators used in problems of decision. We also have set up a generic recommender system whose choice of the aggregation operator is transparent for the user and is able to handle various problems of decision making, such as quantitative or qualitative problems. We use a collaborative model when choosing an aggregation operator in a decision support problem and a degree of satisfaction of the chosen operator. In the future, it will be reinforced by the integration of other aggregation operators and other decision-support concepts, such as the bi-capacity concepts [11]. It would also be interesting to propose new fuzzy measurement identification algorithms, faster and more robust, which tends to be greedy in time with a high number of criteria.

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