Individual and Collective Preferences in MCDA

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Abstract. In this short paper, we propose to include collective preferences in a multiple-criteria decision aiding process, in addition to the individual preferences of the decision maker. For certain kind of decisions, such as the selection of some service providers, the opinions of other previous users can be of great interest when finding the best alternative. Such opinions can be found in social networks, which can be exploited to add new criteria to the model.

1 Introduction and motivation

Multiple-criteria decision analysis tools (MCDA) can be used in many kinds of decision problems. The availability of a computer implementation of many MCDA methods (e.g. by using the Diviz webservices [8]) has started to make its use possible in many applications and in different domains. Their use in online recommender systems is an example of how MCDA methods can improve decision processes that take place within a more general methodology [1, 2]. The case of recommender systems is also interesting because it changes the traditional view of the "decision maker" as a company manager, an administration board or a project director. MCDA now can serve to any kind of decision maker and, particularly, the users of recommender systems are people that search a good option from a large set of possibilities. In such kind of framework, the purpose of the decision is not a key strategic goal, but just to find an appropriate restaurant, a film for the weekend, a new phone or a place where to spend some holidays. In such approach, the user can be denoted as "customer" because he/she is searching for a product or a service provider that fits with his/her individual preferences.

It is well known that customers take into account the opinion of other people about the alternatives that they are considering. We will call them collective preferences. Searching for opinions in social networks is quite common nowadays. We can find many Web places that enable to give a rating about products or features of products (e.g. the price, the service quality, etc). Moreover, many of them give the possibility to write a comment about the products, such as Tripadvisor or Booking. This kind of data available in social networks could be exploited to improve the quality of the outcome of an MCDA process.

In the rest of this paper, a system to analyze the data of user’s opinions and transform them into collective preference criteria is presented. Then, a way of using those criteria in MCDA is proposed, showing an example with the ELECTRE-III method.

2 Sentiment analysis for knowing the collective preferences

With appropriate parsers, one can access the information about ratings and reports written on Web portals. Many of these Webs provide interesting information because you can see the ratings of other previous customers, as well as written reviews that give some personal opinion about their experience. The set of ratings given by the users are usually also aggregated and published as an average, although it is also possible to see each individual vote. However, reviews are shown in a list. Reading lots of reviews is a tedious and time-consuming task. Therefore, even though there is a large piece of high-value information, it is hard to access it when the number of reviews is large. Figure 1 shows a review published at Tripadvisor about a Mediterranean cruise. The text shows a positive opinion about the entertainment activities (pools), an overall neutral experience with the visited places (nice in Mykonos and Athens, but worse in Katakolon and Albania, and finally a negative evaluation of the services of transportation in the ports. The global score is 3 out of 5.

**Figure 1.** Rating and review of a cruise

Sentiment analysis tools have been developed in the last years to perform an automatic extraction of the polarity of opinions expressed in a text [7, 6]. The simplest techniques assign an overall sentiment to a text, being positive, neutral or negative. Another approach, known as Aspect-based Sentiment Analysis (ABSA), assigns these sentiments to certain aspects (i.e. targets) within the text. Taking the example of the cruise review, we have seen different sentiments towards the aspects Entertainment, Visits and Transportation. Aspect-based sentiment analysis methods [10, 9, 4] use a manually labelled data set of texts to train a classifier that distinguishes the sentiments.

Consequently, it is feasible to automatically obtain an estimation of the sentiment expressed by a person in relation to a particular target in a review. If a set of reviews about the same target are analysed, the classifier will give us a numerical rating for each aspect. In [5], we proposed an index to measure the polarity of the sentiment taking into account a collection of reviews, from 0 units (maximum negative opinion) to 100 (maximum positive opinion).
3 Individual and collective criteria in a decision analysis procedure

MCDA methods analyse the values of a set of criteria to find the best solution to a decision problem. Usually criteria correspond to a set of attributes associated to the product that is analysed, and for which the decision maker can establish a preference among their values [3]. For example, the duration of a cruise, the company providing the cruise, the date of departure, the visits included, etc. The performance of a product regarding a criterion can be expressed by means of utility scores or can be directly evaluated in its domain units (i.e. number of days, number of visits) as it is done in outranking models. The individual opinion (i.e. interest, preference) of the decision maker is used in the evaluation of the performance of each alternative.

In this paper, we propose to include also criteria that evaluate the performance of some aspect of the product in terms of collective opinion. The performance of a product will be measured taking into account the reviews made by a set of people that know the product. As explained in the previous section, ABSA techniques can be applied to a collection of texts to extract a numerical polarity indicator of the preference or sentiment of a set of previous customers. This technique can be used in a group of different aspects, generating a group of new criteria that come from the social opinion of the alternatives in study.

Figure 2 illustrates the proposed idea. The set of $n$ criteria is composed by two types of criteria: individual and social. Individual criteria evaluate the performance of the alternatives by considering the preferences of the decision maker (a single person or a team). These performance values are found in the first $c$ columns of the input matrix. Next, we have social criteria that express the sentiment found in social networks, which are found in columns from $c + 1$ to $n$.

Depending on the MCDA method used, other parameters must be fixed. In the example, we show the case of generating a ranking with the ELECTRE-III method with pseudo-criteria. In that case, the indifference, preference and veto thresholds are established for each of the individual and social criteria, depending on their units of measurement and the tolerance-strictness the user wants to consider. In the case of social criteria, the sentiment polarity index will have units from 0 to 100, so the thresholds must refer to that scale. In Figure 2, the model is more strict for Service criterion that for Food, for example. Another parameter is the weight of each criterion, which should take into account the contribution that we want to give to each criterion. The weight of each of those two parts may be different for different applications and should consider too the number of criteria of each type.

Therefore, from the point of view of the MCDA method, it is not necessary to make any distinction in the source of the criteria. The role of each criterion in the analysis will be established by the parameters used and its interpretation in the final result is left to the user.

The authors have used this approach for the case of recommendation of restaurants in the city of Tarragona, using a system called Sentirank [5]. In that case, a set of 6 attributes of a list of restaurants were extracted from TripAdvisor, which conform the individual criteria. Some user profiles were then defined, with different thresholds and weights. Then, using the ABSA methods (in particular, using Support Vector Machines classifiers), a set of 5 social criteria were included in the data set. Results indicate that the ranking of restaurants is quite different when social criteria are considered in the model. We find cases of restaurants that decrease its position in the ranking due to negative opinions of the customers, while some others increase their initial ranking when positive social opinions are introduced.

4 Conclusion

We have proposed a new type of criteria to include when a decision-maker considers that the opinion of other people about the alternatives is essential. We have briefly described how this social opinion can be automatically extracted from short reviews available in social networks. Afterwards, several different MCDA methods can be used on the performance matrix. We have briefly outlined the case of ranking with ELECTRE-III, but selection or choice methods could also be applicable. We believe that this kind of social information may be useful in some application domains. We plan to further investigate this line. The main current limitation is the reducing of different opinions of an aspect into a single number which does not reflect the number of consumers or the diversity of their opinions. Moreover, in practice, a decision-maker might wish to assign more weight to those collections of reviews expressed by consumers with profiles closer to their own. We plan to address these issues in our future work. Furthermore, we plan to adapt the system to differentiate between the reviews based on the consideration of the profile of the decision-makers (e.g., age, sex, nationality).

REFERENCES


