Application of Learning Methods in MCDA models: Overview and Experimental Comparison

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Many real world application lead to a multicriteria decision problem all in the medical, the financial and the engineering area. When there is a set of alternatives described by a set of criteria (attributes) and either sorting, ranking or making a choice is requested by the decision maker while all the criteria have to be taken into consideration, there is a multicriteria decision problem.

In multicriteria decision aid (MCDA) models usually numerical (continuous) inputs are handled, as value functions, orderings on a real interval or preference intensities. One of the simplest – and most commonly used – model we can imagine bases on the aggregation of value of each criteria, for example $\sum_{i=1}^{m} w_i g_i(\mathbf{x})$, where $g_i(\mathbf{x})$ is the value of alternative $\mathbf{x}$ on the i-th criterion and w_i is the importance of the i-th criterion[2].

On the other hand, usually learning or classification methods, from the field of artificial intelligence, can detect relationship among elements of an input dataset described by a set of categorical (discrete) criteria, like hierarchical classifiers, decision trees (ID3). Using a decision tree, the class of an alternative can be easily predicted starting from the root node of the tree and applying the tests specified in the inner nodes of the tree. After the appropriate branches of the nodes had been chosen, finally a leaf node is reached which gives the class of the observed alternative.

In order to apply these methods in decision aid models they had to be extended to work on numerical criteria, both in the model building phase and later, in the application one. In the well-known C4.5[6] method it can be solved only by discretization of values of numerical attributes, while in our Continuous Decision Tree (CDT) building method, introduced in [5], it is not necessary. It builds a decision tree using the numerical domains. In addition, in our method the possible tests – that are applicable in the inner nodes of the tree – are also enlarged, while keeping them still meaningful and interpretable for the decision maker. This is also important to avoid black-box effects.

We examine the applicability of learning methods, like CDT, in decision support systems to build MCDA models and give an extended empirical and numerical comparison of our method to some other ones, for example C4.5[6], CID3[4], SVM[7], CART[3], on some artificial and real life classification tasks[1].

Keywords: Multicriteria Decision Aid (MCDA), Decision tree, Continuous Decision Tree (CDT), ID3, C4.5, Continuous ID3 (CID3), Support Vector Machine (SVM), Classification and Regression trees (CART), Pattern recognition.

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