The use machine learning interpreter for the development of decision support system

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Abstract

Multi-criteria decision support systems (MCDSS) use expert knowledge that gives a subjective nature to the decision-making process. The complexity of expert judgment increases significantly with an increase in the number of parameters considered. These shortcomings lead to the search for other decision support methods that would be less sensitive to the opinion of experts and could process large amounts of data with a large number of heterogeneous properties. A supervised learning provides this opportunity. We propose the general schema of incorporation machine learning (ML) methods and ML interpreters to decision support process.

Keywords: machine learning, multi-criteria decision support system, machine learning interpreter, SHapley Additive exPlanations (SHAP).

1 General

Traditionally, MCDSS use knowledge of experts that are consolidated to form a solution. The methods of obtaining knowledge include: AHP (analytical hierarchy process) [1], PAPRIKA (Potentially all pairwise rankings of all possible alternatives) [2], PROMETHEE (Preference Ranking METHod for Enrichment of Evaluations) [3], TOPSIS (method for the solution) [4], ELECTRE [5]. The solutions listed above are used to form the solution, as well as Weighted Linear Combination (WLC), Ordered Weighted Averaging (OWA) [6], Bayesian networks [7, 8], fuzzy logic [9], etc.

Despite the solid theoretical baggage, for MCDSS, using the knowledge of experts, there is more or less characteristic subjectivity in the decision-making process. In addition, with the increase in data volumes and the number of features taken into account, the complexity of expert assessment itself increases significantly. For example, the AHP technique requires $k = \frac{[\![(n)]\!]^2 - n}{2}$, pairwise comparisons for n features, which can significantly complicate the work with n> 100. These shortcomings make it necessary to look for other decision-making support methods that would be less sensitive to the opinions of experts and could process large amounts of data with a large number of heterogeneous features. Supervised learning method provide this opportunity. However, until now, the use of machine learning models encountered the problem of "black boxes", that is, the inability of many algorithms to give explanations to the result obtained. Only recently obtained results in the development of explanatory systems [10, 11] allow not only to apply them to assess the weight of machine learning model features, but also, in our opinion, to use them in the decision support process.

Our approach, which may be called MCDSS based on the explanation of "black boxes" (MCDSS&BBE), consists of the following key elements (Figure 1).

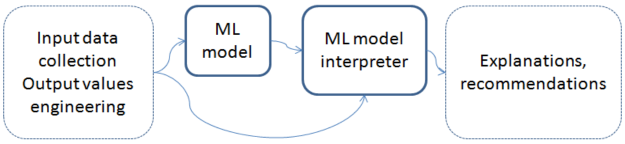

Figure 1 MCDSS&BBE workflow schema

First, we collect input data and determine the target parameters.

Second, we build a non-linear model based on supervised learning method (ML model), in which we take into account the maximum possible number of features.

Third, we estimate the weight of the contribution of the features to the result achieved by the model as a whole and by the individual object (ML model interpreter).

Fourth, we use interpretation results to develop recommendations.

That is, the model is interpreted to answer the question "Why do we have one or another result of classification or regression?". The answer to this question for an individual object is essentially some recommendation for changing parameters in order to increase the values of target parameters.

We tested this approach using the SHapley Additive exPlanations (SHAP) [11] interpreter to make recommendations in the field of school education according to National Educational Database (NEDB).

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